A hedonic model of Canadian dairy farmer Holstein-semen purchases

by

Aggar Alexandra Frías Luna

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Department of Resource Economics and Environmental Sociology
University of Alberta

ABSTRACT

The dairy industry in Canada has undergone huge changes in the last few decades. While the average annual milk production per cow grew over three times by 2015 (average rose to 8.65 Hectolitres per and reached 9.5 Hectolitres in 2018) from 1995 levels (2.5 Hectolitres a year per cow on average), the number of farms across the country continues to shrink. One key element of change may concern the genetic makeup of the cow herds: Canadian farmers have succeeded in producing higher-yielding cows through their breeding choices. Moreover, the incorporation of genomics into the toolset of sire selection in 2008 brought new possibilities to attain genetic gains in cattle herds. Semen selection decisions are hence critical to dairy operations' efficiency and productivity levels.

Characterizing farmers' preferences towards the different sire traits during sire selection can help describe the importance of particular traits in the industry and ultimately, continue to move the dairy sector towards sustainable efficient production.

Canadian dairy farmers' preferences for sire attributes before and after the increased use of genomic technology are studied to help understand producers' breeding decision-making process. This research is aimed at evaluating trait importance in sire selection decisions and if a shift in trait valuation is observable with the use of genomics from 2008, when genomic tools became more widely used in Canada, to 2016.

Following Richard and Jeffrey's (1996) last analysis of dairy farmers' valuation of sire traits in Canada, this study expands the application of econometric estimations on market transactions of Holstein semen to examine dairy farmers' preferences for the different production and type traits. The hedonic price modeling performed in this study offers an update of Holstein sire trait valuation for the average Canadian dairy farmer over the course of eight years, those immediate to the introduction of genomics. A variety of econometric functional forms will be used to characterize demand for sire traits. These models will allow the industry to better understand the demand for specific traits, predict future trait demands and ensure that genomic analysis focuses on traits of significant interest to producers.

Key words: genomics, sire selection, farmer behaviour, dairy industry, Holstein cows, livestock, cattle, Canada, Lifetime Profit Index, LPI, Production economics, agriculture economics, resource economics, Hedonic Price Model, Semen Cost model, MLE, Tobit I, Cragg Double Hurdle, corner solution model, two-part model, Unbalanced panel data series, pooled data series, Stata.

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Table of Contents

List of Figures

List of Tables

Chapter 1 . INTRODUCTION

A. INTRODUCTION

Genomic innovation presents opportunities for farmers, processors and retailers to improve the attributes of their livestock output and increase that same output, through breeding decisions. In other words, genomic selection allows producers to make decisions that can improve their herds without waiting for their chosen dairy sires to be proven by obtaining phenotypic data from 100 daughters, while still providing high quality affordable dairy products to consumers. More specifically, genomic selection allows for animals and plants to be chosen based on the prediction of "additive genetic merits [known as genomic estimated breeding values (GEBVs)]," and achieve an enhanced improvement of low and moderately heritable traits (Taylor et al., 2016, p.7690). And yet, it is the very adoption of this technology which poses many questions. While scientists search to find a way around the methane emission levels of livestock operations, the level of adoption of genomic innovations themselves (like genomically identified, low methane-producing bulls) is uncertain. The adoption of new breeding technologies can be deterred by attitudes among the public and public disapproval towards the use of genetic or genomic tools in the food chain as well as producer reservations towards innovation. Therefore, uncovering the attitudes of producers about genomic technologies is increasingly important to understand the likelihood of adoption in the production system. The better we can identify dairy farmers' preference structures for cow traits and the more we know about the demand for specific traits, the better able we are to ensure that genomic analysis focuses on the traits of significant interest to producers and speeds up the rate of progress in productivity, as well as conformation and animal health in the dairy industry.

As dairy producers face challenges in optimizing their operations to remain profitable and in satisfying public demands for greener methods, genomic innovations in breeding have the potential to surmount the ceilings they currently encounter in their production. Nevertheless, as we will emphasize in detail in the later sections, cost minimization or revenues are not the only objectives that producers, scientists and economists have in mind, but rather an all-encompassing solution that leads to a gain in society's well-being. As Genome Canada surmise in their GE^{3}LS acronym, the main aim is to find alternative technologies that bring about the greatest societal benefit in terms of sound genomics, as well as ethical, environmental, economic, legal and social considerations.(Genome Canada, 2017).

In a national survey discussing cattle health in 2016 (Bauman et al., 2016), Canadian dairy producers "ranked reproduction as the most important priority for research" (Denis-Robichaud et al., 2018, p.852). In addition, breeding decision-making was ranked among the top three reasons for farmers to consider the use of genotyping services for their herds in Hailu et al.'s (2016) survey of Ontario dairy producers. Additionally, studies by Vishwanath (2003) and Howley et al. (2012) supported the assertion that breeding input costs, like semen and insemination itself, as well as their rates of success, play significant influencing roles in the adoption of breeding technologies like artificial insemination (AI). Nevertheless, the costs of using genomic tools in breeding dairy animals (and other livestock) are falling. In February of 2019, the price of genotyping tests (which capture many traits of interest to dairy producers) further dropped to $33 for testing with a low density panel (Harris, 2019). Clearly, the cost of breeding inputs and genomic testing, and their *perceived* degree of profitability need to match in order for producers to feel comfortable in investing in these technologies.

The main objective of this research is to uncover producers' behaviour towards the adoption of new genomic technologies in breeding and assess if there is a discernible difference in adoption behavior over the past decade after the deployment of genomic selection started in 2008. Specifically, this study will identify which breeding traits are of particular interest to Canadian dairy producers and indirectly assess the effect that the introduction of genomic information has had on dairy farmers' breeding decisions. This analysis will be pursued through the use of actual semen transactions over time. Selection decisions set up the entire dairy operation's production and financial potential for several years (based on the new replacement cows derived from the genetic makeup provided by the selected bull semen purchases used in artificial insemination). Since Holstein cows represent over 90 percent of the nation's dairy herds (Holstein Canada, 2015), this analysis will base its observations on this breed's semen transactions. By focusing on semen purchases at discrete points in time, this study seeks to find if the values conferred on the main bull attributes have changed over time, focusing on the period after the inclusion of genomic information for sire selection. An additional objective of this analysis is to assess if the preference for the key sire attributes for semen selection have changed significantly from year to year.

Finally, the weights of these attributes in the formulas for the main Canadian indicator, the Lifetime Profit (Performance) Index (LPI), will be compared against the findings of this study's estimations to assess the extent to which the behaviour extracted from market transactions is reflected in these economic index created by the dairy industry. Are the index values associated to bull semen samples accurately representing the information that producers prioritize to make a decision about semen purchases?

The last objective of this study is, therefore, to examine if the weights used in the indices align with farmers' ranking of bull attributes during their bull selection decision by comparing the econometric results of the hedonic values of semen attributes over time to the attribute weights included in the Lifetime Profit (Performance) Index (LPI) index. As the third most important agricultural sector in Canada, reconciling the trends observed in bull proofs from the last decade with the information extracted from market transactions is not only valuable in accurately describing Canadian dairy producers' reasoning and priorities in the literature: Producer breeding choices are also of special interest to bull breeding companies, cattle producers, processors, other associated industries, as well as government offices in charge of setting mandates, laws, extension programs and incentives in the dairy industry.

B. BREEDING PROCESS: CANADIAN BREEDING SERVICES AND DECISION-MAKING

Despite observing an increasing trend of revenue and average milk liters produced per cow over the recent decades, the number of farms and herd sizes in Canada have consistently diminished from their 1970s values[1]. On a national level, the number of dairy cows recorded in 2017 was 956 900, or merely 41.7 percent of 1970's total of 2 295 000 head of cattle (CDIC, 2020a)[2]. Further, as highlighted above, the number of farms contracted staggeringly by 91.1 percent, from 122 914 in 1970 (CDIC, 2020b) to 10 951 in 2017, and to 10 371 by 2019 (CDIC, 2020b). As Canadian dairy producers face a changing import regime and the costs of purchasing quota units to expand their production, their operations face an ever-increasing pressure from downward price trends in the market and the need to maintain or improve their bottom-line profits.

According to Murray Hunt, a geneticist and previous general manager of Holstein Canada's extension services in Ontario (Ontario Holstein, 2017), the genetic improvement of a herd is dependent on sire selection

[1] On August 1st, 1970, Canada had 122 914 farms with shipments of milk registered. By August 1st of 2018, the number of farms registered shrunk to 10 679.(CDIC, 2020b)
[2] 2019 recorded 968 700 milking cows by January 1st, (CDIC, 2020c).

by 85-90 percent (Hunt, 2019b). Further, Hunt (2019b) affirms that, “if a herd’s genetic level is not improved, the herd will fall behind other herds and the dairyman will be at a disadvantage in the efficiencies that higher genetics bring with them”. It is clear, therefore, that the success of genetic improvements in dairy cattle progenies is of crucial importance not only for farmers and dairy-related players, but also to the Canadian economy. The release of “the first high-density genotyping chip for an agricultural species, the Illumina Bovine SNP50” in January of 2008 allowed for the increased use of genomic selection in breeding decisions, and facilitated efforts to improve moderately-heritable production traits and lowly-heritable type traits[3] (Taylor et al., 2016, p.7690) (e.g. production traits (milk, fat, protein) (moderate) and somatic cell score (SCS), fertility and longevity (low heritability), García-Ruiz et al, 2016; Miglior et al., 2017). Understanding the rationale behind the breeding choices made for herd replacement after this breakthrough is thus pivotal to securing the progress of the dairy industry and Canada’s market share in the decades ahead.

1. Breeding beyond the farm gate: Semen and embryo sales internationally

In 2015, Canada exported $111 million CDN worth of semen samples, with $40 million CDN of the total destined to the US alone (Jokinen, 2016). The sales represented an increase of 24 percent from the $85 million CDN sold in 2011 (Jokinen, 2016). Canadian dairy genetic material is highly regarded, with countries like the United States, Australia, Germany, Japan, the Netherlands and Brazil importing live animals, embryos and semen for their domestic production (Holstein Canada, 2015). One ejaculation of approximately 125 millilitres produces up to 500 straws for sale (Jokinen, 2016). While one unit, or a straw, could range between $25 to $35 CDN, some proven sires with star pedigree like Braedale Goldwyn produced semen vials worth $100 CDN a straw in 2006, and bulls like Lottomax would produce $50 CDN straws and Johnny Cash $24 CDN (Jokinen, 2016). Canadian dairy genetics are highly regarded in the international markets and well sought after for breeding purposes from China to Australia to the European Union (Jokinen, 2016). In fact, the CDN estimates that “50% of the productivity gains being made in Canadian dairy cattle comes as a result of genetics” (Hunt, 2019b).

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[3] *Type traits* describe “skeletal characteristics of an animal” and “are moderately- to strongly-correlated genetically with a range of other performance traits in cattle including feed intake, reproduction traits and carcass merit” (Doyle et al., 2020, p.1). In Canada, the CDN collects scores for a total of 27 different type-related traits, but publishes genetic evaluations with 21 of these, which include attributes like conformation, dairy character, frame/capacity, feet and legs and mammary system (see **Appendix 3** for a comprehensive list of these traits) (CDN, 2000).

On the other hand, the new breeding technologies are also affecting the way cows are bred and replaced in domestic herds. DNA testing allows farmers to select for specific attributes that improve the health and performance of their herd (Harris, 2019). Since embryos can now be submitted to a biopsy and genotyped to extract their genetic potential profile with (a) 70 percent reliability, most AI companies as well as foreign markets, like China, are opting for this option (Greig, 2018). Superior embryos can be fertilized under lab conditions through In-Vitro Fertilization (IVF) with high-grade semen (Greig, 2018). Although commercial milk cow sales are still prevalent across Canada and the world market, the use of genomic technologies has changed common practices. By 2014, however, more than 50 percent of the semen sales around the world were from genomically-tested sires instead of proven sires (Hunt, 2014). Beyond the profitability of Canadian dairying operations, it is evident that breeding decisions in Canada are valuable for the international market and trading, if the genetic material is to remain competitive on the world market.

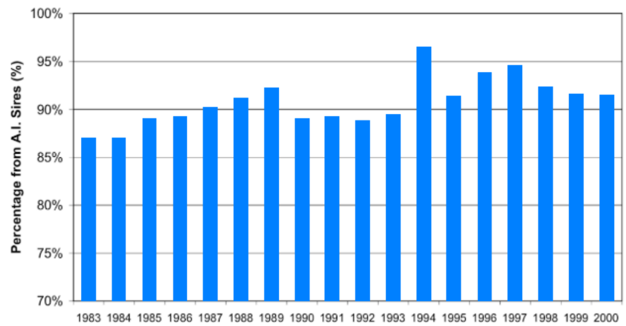
2. Genomics: The changing landscape of bull breeding

The milking cows of the current dairy industry have come a long way from those in the 1960s. The modern dairy herd cycle usually starts with heifers that give birth after nine months and are ready to be milked after a week of colostrum milk is finished (Les Producteurs du Lait du Québec (PLQ), 2019). Milking is continued for the next ten months, or 300 days, until it is time for another insemination period (PLQ, 2019). Cows continue to lactate through their pregnancies, but milking is stopped in the last two months before they give birth, and then, the cycle repeats (PLQ, 2019). In general, cows are milked for four lactation periods and a farmer replaces a quarter of the herd every year to maintain consistent production levels (PLQ, 2019).

In contrast, the cows of the first half of the 20th century would begin calving around the 27-28 months and about twice the amount of today's calf numbers would die before weaning (Hunt, 2019a). In addition, only 10 to 20 percent of the first-time heifers would be outstanding, while a high proportion of these would be culled; up to 30 percent of these would have difficulties with calving, low milk production, low fat testing results, or physical issues like deep udders or weak median suspensory ligaments (Hunt, 2019a). These cows would still follow a "dual purpose" objective and were thus "shorter, beefier, had udders that deepened quickly with age and they produced half as much milk (35 pounds per day from first calving to herd removal)" (Hunt, 2019a). When it came to selecting a bull, farmers would only trust on proven sires and would not bid on young sires unless companies would heavily incentivize them to take the risk of investing in them instead (Beavers and Van Doormaal, 2019).

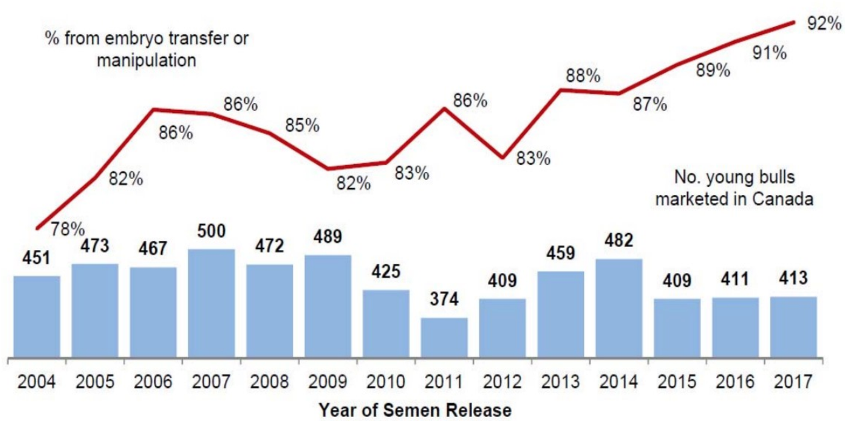
Although artificial insemination was brought forward since 1899 in Russia, the practice did not come to Canada until 1936 (Van Doormaal and Kistemaker, 2003) and it did not gain popularity in North America until the 1960s (Jokinen, 2016; Van Doormaal and Kistemaker, 2003). When genetic testing started, Artificial Insemination (AI) companies would purchase bulls and wait for their return on investment to pay off; after the sires had reached sexual maturity, farmers needed to be encouraged to use the young sires to breed with their cows (young sires were *unproven* by data related to the productivity of at least 100 of their daughters), and once the nine months of gestation were over, the calf would still need two more years to be ready for calving and to start milking (Greig, 2018). Genetic information was based on parent/daughter productivity averages, and it was only 35 to 40 percent accurate (Greig, 2018). Sires would normally be bred by artificial insemination companies as well as by breeding farms, traditionally based on phenotypic (daughter) data (Van Doormaal and Kistemaker, 2003). Historically, the Canadian Dairy Network issued proof reports every three months with genetic evaluations of the sires in the market, but with the quick turnaround of daily selection for bulls and their mothers, the reports became weekly issues (Greig, 2018). In Canada, the practice of AI use reached 50 percent usage level in 1975, and after attaining 75 percent usage by 1985, it "tended to plateau"(Van Doormaal and Kistemaker, 2003). The percentage of Herdbook-registered animals that were sourced from AI sires first reached 90 percent level in 1987 (Van Doormaal and Kistemaker, 2003). The advent of the Illumina BovineSNP50 in 2008, the first high-density genotyping chip, equated to progeny-testing of 11 daughters and opened way for two-year-old bull semen to be marketed for sale (Taylor et al, 2016). Nowadays, young sire semen has taken up to 70 percent of the semen market share (Beavers and Van Doormaal, 2019).

Figure 1.1. Percentage of dairy cattle registration in Canada from artificial insemination sires, 1983-2000 (Van Doormaal and Kistemaker, 2003)



In fact, the proportion of semen units sold in Canada swung from the original share distribution of 20 to 30 percent sourced from genomic young sires and 70 percent from progeny-proven sires to the very opposite ratios (Greig, 2018). The CDN restated this shift in 2019, as it observed close to 70 percent of the Canadian semen market was taken up by young sires (Beavers and Van Doormaal, 2019). The industry attributes the swap to the fact that genetic merit values can now be found with a 70 percent level of reliability, as opposed to the initial 35 to 40 percent value when commercial genotyping of semen samples started in 2009 (Greig, 2018). As a result, genetic companies have favored purchasing semen units over physically owning bulls, and many bull barns have closed throughout the country (Greig, 2018).

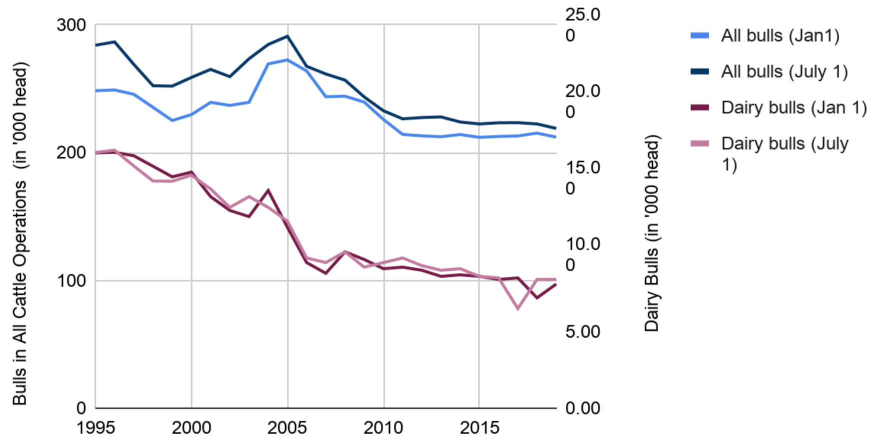
Figure 1.2. Number of Holstein genomic young bulls marketed in Canada vs the percentage resulting from Embryo Transfer or Manipulation



Source: Beavers and Van Doormaal, 2019.

In the last two decades, the Canadian inventory of bulls halved from the 15 400 head in stock in the year 2000 to 8 100 by 2019 (StatCan, 2020).

Figure 1.3. Number of Dairy Bulls vs. All Bulls (1 year or older) in Canada, 1995-2019



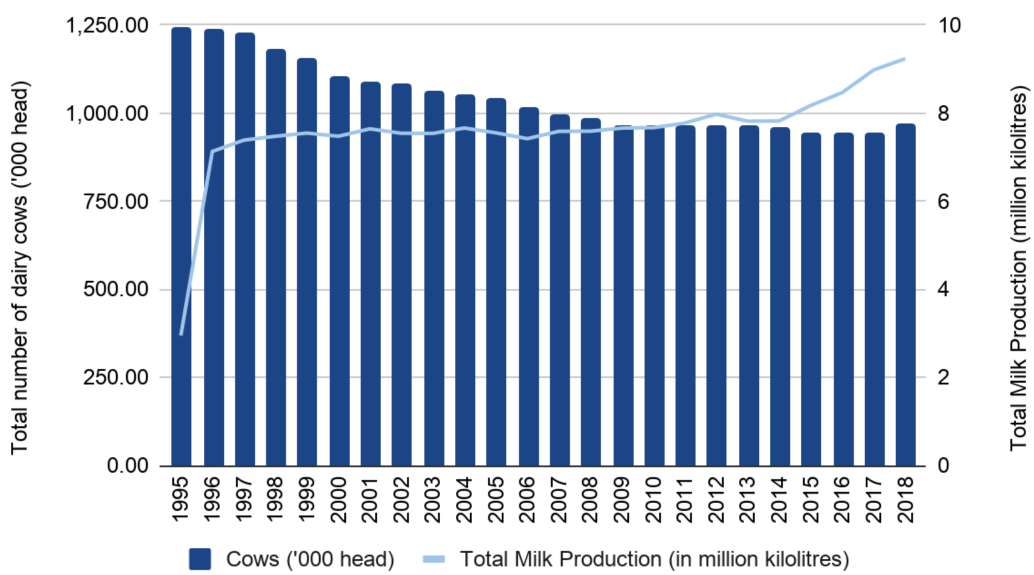
Source: StatCan, 2020. Table 32-10-0130-01

Further, Beavers and Van Doormaal's (2019) analysis of the Canadian semen market for Holstein Genomic Young Bulls shows a rising trend in sires sourced from embryo transfers or manipulations such as embryo splitting; from 78 percent in 2004 to 92 percent by 2017 (see **Figure 1.2**). Germain Lehoux, a previous president of Holstein Canada, could only account for two private farms left in Canada servicing these genetic companies, Westcoast Holsteins in Chilliwack, BC and Stanton Farms in Idlerton, Ontario (Greig, 2018). Furthermore, the CDN's analysis of breeder prefixes on Holstein bulls found that 47.9 percent of the bulls being used for AI in Canada in 2017 were sourced from only 10 breeder prefixes, as opposed to the 19 percent to 28 percent range that had been observed between 2004 to 2017 (Beavers and Van Doormaal, 2019).

3. Bridging trends in current productivity volumes with results from economic analysis

The Canadian Dairy Commission (CDC) (2017b) noted that total milk production across Canada grew by 8.9 percent between 2011 to 2016, from 77.8 million hectolitres to 84.7 million hectolitres, while the total herd numbers remained closely similar (only a 0.6 percent drop in stock numbers). Nevertheless, the number of farms has diminished over this time, and the number of cows per herd has increased by 12.1 percent in this same period, increasing to an average of 85 cows per farm (CDC, 2017a). The trend in rising production against falling farm numbers has continued, with milk production reaching 92.4 million hectolitres in 2018 (CDIC, 2018) while still experiencing a 2.9% shrinkage in the number of dairy farms (329 dairy operations were lost) (CDC, 2018a). Interestingly, national censuses continue to highlight a *fall* in the number of dairy cows (by 3.8 percent in 2016 from 2011), reporting them against a consistent increase in annual milk production (Statistics Canada (StatCan), 2017). Looking solely at the input numbers and the output volumes, the CDC concludes that, "[d]espite having fewer farms, Canada produces 21% more milk than 5 years ago to respond to domestic demand" (CDC, 2018a).

Figure 1.4. Total number of dairy cows vs. total milk production in Canada, 995-2018



Source: CDIC, 2020a, d. Reports D-042, D-08.

In the last two decades, Canadian milk production has sky-rocketed from 74.8 million hectolitres in 2000 to 92.4 million hectolitres in 2018 (CDIC, 2020d). This phenomenon has been attributed to a gain in productivity per cow through improved "animal nutrition, genetics and production practices" (StatCan, 2017). Similarly, the Canadian Dairy Network (Beavers, 2017) showed a trend in improved productivity after the use of genomic information became available to Canadian producers (Hunt, 2017), suggesting a strong correlation between increased milk production and the use of genomic information for breeding decisions. For instance, Cows born between 2011 and 2016 were expected, on average, to have a rise of approximately 5 kg of protein yield per year in their 305 lactation day cycle against the 2.4 kg expected for cows born between 2004 and 2009 (Beavers and Van Doormaal, 2017). Brian Van Doormaal, the chief executive of the Canadian Dairy Network (CDN) also states that genetic progress of Canadian dairy has doubled since genomic information was included into breeding decisions in 2009 (Greig, 2018).

Nevertheless, the information in regards to this trend in the Canadian dairy industry and farmers' behaviour on bull or semen selection is not extensive nor have the relative trait gains been econometrically-estimated to test for their significance, so reassessing this sire-selection decision with more recent data and analyzing the key attributes comparatively will not only help the bottom line of all key players in the dairy industry, but also support ongoing efforts to select for them through the use of genomics. By focusing on the breeding decision process, we strive to corroborate if these findings linking phenotypic attributes with feed efficiency genes coincide with the attributes prioritized in farmer's breeding choices.

Firstly, this research will assume that producers follow the behaviour outlined in firm theory, where they run their operation to obtain economic efficiency (Doll and Orazem, 1978, 2nd ed.). The model will further assume that farmers are operating under a perfectly-competitive market with risk averse preferences. In Canada, there is no single pricing scheme but instead, semen prices ($/straw) are set independently by each Artificial Insemination unit (Richards and Jeffrey, 1996).This also allowed for the assumption of competitive, open markets to remain valid for the hedonic price modelling.

Upon close inspection of the Canadian dairy market, however, this assumption will not hold, as it is regulated under a supply management system. Thus, the implications of this study cannot be addressed solely using the classic 'blackboard economics' framework of the firm, as Coase (1991 in; Williamson and Winter, 1991) termed it, but merely as the standard baseline from which the research can proceed into deeper analysis. Ultimately, we acknowledge that the different context of the Canadian dairy supply market can also affect their preferences when making their sire selection decisions. Indeed, Just et al. (1982) confirmed that adjusting the assumptions of a model to account for non-competitive markets is of great importance to avoid econometric coefficients to present errors.

4. Market Pressures on Canadian farmers that differentiate their production problems from the rest of the dairy market scenario

The two principles sought with supply management are to restrict domestic milk production and the entry of foreign dairy products (Davey, 2004). As the supply management framework restricts expansion of quota rights, farmers are usually inclined to seek alternatives that do not include tweaking their operation size outside of their allotted quota levels. As a result, they must seek to downsize production costs through other avenues other than targeting the size of their operation. Evidently, Canadian producers face different pressures while striving to attain efficient production and profit maximization for their operations. It is necessary to consider the additional pressures Canadian dairy farmers face as a result of supply management, and how these may account for a constricted set of profit-increasing alternatives in comparison to their American counterparts.

Under this premise, as they cannot look into expanding their operation to spread their costs more evenly through greater herd sizes and their associated greater production levels, we would expect producers to have an additional incentive to be willing to pay for innovations that would lower their costs of production, such as increasing cattle's feed efficiency or the improvement of their herds' health and productivity levels. The latter implies that farmers' behaviour would result in observed preferential selection of cost-cutting or productivity-enhancing traits in their breeding decisions. This is a key consideration to keep in mind when evaluating producer behavior in Canada, as these market conditions set these producers' apart from their American, European or Australian counterparts. Is there evidence to support the assertion that the additional market limitations in the Canadian dairy sector move farmers to favor investing in innovations related to optimizing their operation or to cut down costs of production? Finding an answer to this question is an objective beyond the scope of this current analysis on farmers' bull semen transactions, but which can incidentally take part in the trait preference structure revealed through our analysis.

C. INDUSTRY AT A GLANCE: OVERVIEW OF CANADIAN AGRICULTURAL PRODUCTION

Agriculture has always been a core aspect of Canadian society and economy. Although the dairy sector itself has seen a lot of changes in its spatial distribution nationwide and its operations' production structure, it remains a vital element of the agricultural industry. The aim in this section is to paint the outlook that Canadian producers face in order to better understand their constraints and incentives, as well as to emphasize the relevance of our study within the scope of Canadian society. Firstly, it will touch upon the contribution of the dairy sector to the Canadian agriculture industry and the entire economy. Secondly, a brief overview of the milk pricing system in the country as well as the markets into which producers can sell their milk products is included. The third subsection goes over the broad consumer demands in the country to complete the picture of Canadian farmers' scenario further. Finally, the last section describes the typical operation and compares their herd structure to other nations with comparable settings.

1. The Dairy sector in the Canadian Economy

In 2016, the agriculture and the agri-food system amounted to $111.9 Billion, totalling 6.7 percent of Canada's Gross Domestic Product (GDP) (Agriculture and Agri-Food Canada (AAFC), 2017). By 2018, the sector's contributions rose to $142 Billion[4] and maintained its share in the national GDP.[5] Clearly, the agriculture sector continues to maintain its average contribution to the Canadian economy in recent years, as it has for the last decade, ranking as the seventh key industry for the entire Canadian economy and held a similar value on the provincial level (see **Appendix 1**, AAFC, 2017, pp.41, 42). Further, this sector was the second largest source of employment nationwide, as only the Health Care and Social-Assistance sector surpassed the 2.3 million people across Canada that participated in an agriculture or agri-food field (see **Appendix 1**, AAFC, 2017, p.44; Government of Canada, 2019).

Focusing on the dairy sector, the Agriculture and Agri-foods Canada (AAFC, 2017) reported it as the third largest contributor of the total agricultural market receipts after the grains and oilseeds industry and the red meats sector. More specifically, net dairy cash receipts totalled $6.2 Billion in 2016, representing a 10.7 percent share of the $57.6 Billion total net agriculture market receipts (AAFC,

[4] Government of Canada, 2019.
[5] Extrapolated from Ontario Ministry of Finance, 2019.

2017). This share remained unchanged in 2018, as the total dairying cash receipts contributed $6.6 Billion (CDIC, 2018)[6] to the $62.2 Billion total farm cash receipts (StatCan, 2019). In addition, dairy manufacturing shipments contributed 13.8 percent to the Canadian total in 2016 ($14.8 Billion, AAFC, 2017) and 12.8 percent of Canada's $115.6 Billion manufactured shipments in 2018 ($14.8 Billion, CDIC, 2018).

Nevertheless, the impact of the dairy industry cannot be measured strictly on direct farming operations and processing alone. The dairy sector employed close to 221 000 people throughout the entire supply chain[7], with 22 904 people working for processing purposes around the country[8], and 18 805 (CDIC, 2018) people were involved farming-related jobs, Quebec alone reported 83 000 workers engaged in dairy-related occupations (PLQ, 2018b) while Ontario registered 74 000[9] jobs in this field. It is evident, therefore, that the degree of influence this sector plays on the different regions of the country is not the same.

2. Canadian dairy: Milk markets, classification system and sales

Canada has two domestic markets for milk; the fluid milk market for consumer's milk beverages and fresh cream, and the industrial milk market for the further processing into dairy goods like butter, cheese, yogurt and ice cream (CDC, 2017b). Approximately a third of the national production is destined to the fluid market (approximately 97.8 million kilograms of butterfat), while the other 71.1% of milk produced (240.2 million kilograms of butterfat) is used by processors in the manufacturing of dairy products (CDC, 2017b).

Further, milk is divided into separate classes under the Harmonized Milk Classification System (CDC, 2018b). They differentiate their type, quality, price and further dividing them in subcategories by their specific final product characteristics (see **Appendix 2** for a comprehensive list of the milk classes). The shares of the national production for these main dairy products for 2018 broken up by the province

[6] Also see Government of Canada, 2020.
[7] 2015 data reported 220, 936 working in the dairy sector (Dairy Farmers Canada, 2018).
[8] Canadian Dairy Industry, 2017
[9] Dairy Farmers of Ontario, 2018.

of origin or region can be seen in a graphic representation on **Figure 1.5.** Further, a sample breakdown of annual provincial dairy production for 2017 and 2018 is also available on **Figure 1.6**.

Milk pricing in Canada is generally based on its components; butterfat (F) and non-fat milk solids (solids non-fat, SNF) (Friesen, 2013). While the decades of the 1970s and 1980s saw a consistent effort to increase protein production and lower milk fat (Kennelly et al., 2017; Hunt, 2018), the later decades saw a steady rise in the demand of milk products like cheese, and a fluid milk consumption decrease (Mussell, 2016; Hunt, 2018). Cheddar and specialty cheese production, for instance, increased by 12 and 15 percent, respectively (Mussell, 2016). Nevertheless, it was evident that "domestic skim milk use has not grown commensurate with growth in cheese production" (Mussell, 2016, p.4). Consequently, Canada's multiple component pricing system in Canada emphasized butterfat selection by valuing butterfat above the solids-non-fat (SNF) component of milk (Friesen, 2013).

In 1993, milk component pricing shifted payments away from a volume-based system (with a butterfat differential) to separate rates for butterfat, protein and the other milk solids (solids non-fat SNF) (Kennelly et al., 2017, p.13). At the end of 2004, on December 1st, a set of policies were set in place to tackle the increasing surplus stock of SNF. Producers with extremely low butterfat shipments were targeted and encouraged to increase their production with a minimum 3.25kg/hL butterfat policy; a $3/kg reduction in the protein payments (added to butterfat instead) and; the introduction of an SNF:BF ratio (Kennelly et al., 2017,p.15). Lastly, in December 2015, the Canadian Dairy Commission announced a rise of 5% in butterfat support prices but a 30% reduction in support prices for Class 4(a) skim milk (Mussell, 2016, p.3). Ultimately, it can be gathered that the prices of each milk class will work as an incentive for producers to seek to deliver milk at the highest-earning category, and thus, their herd performance will also be fine-tuned to produce the milk attributes that are highest grossing. Nevertheless, it must also consider the significant time challenge implied in adjusting breeding objectives to align to changing prices, since building herds to produce milk at high productivity with varying components requires several years until replacement cows become productive dairying members of the herd.

3. Production trends

At the start of 2017, the Canadian Dairy Information Centre (CDIC) (2018) reported a total of 1.4 million dairy cows and heifers were used to fulfill the country's dairy production plans. On average, Canadian farms have herd sizes of 84 cows (PLQ, 2018b). Nevertheless, Quebec, the largest provider of cheese and yogurt in the country[10], holds a smaller mean of 70 cows per herd with an average annual production of 600 000 litres of milk and a total production of 3.3 billion litres from the province for 2018 (PLQ, 2018a). Ontario, on the other hand, holds the first place in milk and cream production since 1977[11] and has an average herd size of 88 cows per farm[12] and an average annual production 814 440 liters of milk[18], with an overall provincial milk production of 2 942 572 296 liters in 2018 (Ontario Dairy Farmers, 2018). Together, the two Central Provinces contributed 70 percent of the milk in Canada for 2018 (PLQ, 2018c).

Over the years, Canadian milk total production (as well as production per cow) has soared from 76.95 million hectolitres (CDIC, 2020e) with 3 107 800 milked cows in 1959 (StatCan, 1960) to 89.8 million hectolitres using only 945 000 dairy cows in 2017[13]! By the end of 2018, milk production was 92.4 million hectolitres, although the number of cows did increase to 972 300 (CDIC, 2020d). Nevertheless, while the dairy industry's revenues grew at a 2.5 percent rate from 2008 to 2015 (Tack, 2017), national milk production has experienced a consistent rise in total volumes against decreasing cow numbers since 2010 (see **Figure 1.4** above). Moreover, forecasts from Farm Credit Canada (FCC) (2018) measuring milk production growth on the farm gate recorded an average of five percent rise in yield levels per year for the 2014-2017 period, and expect the growth trend to remain on the same level. As a result, provinces like Manitoba and Ontario have already started investments for building more and expanding existing milk processing infrastructure and thus keep up with the increased milk output levels and the higher market demand for dairy products in the country, (FCC, 2018).

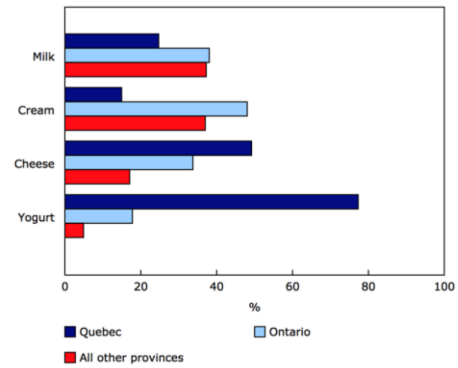
[10] Quebec is responsible for 53 percent and 76.7 percent of the cheese and yogurt national shares, respectively (PLQ, 2018c). In fact, Quebec has held the first spot for cheese and yogurt production since 1986 and 1987, respectively (PLQ, 2018c).

[11] Ontario produced 37.7 percent and 48.4 percent of all Canadian milk and cream, respectively (PLQ, 2018c).

[12] Arnason, 2018; CDIC 2020a, 2020b. 820 572 liters if using the 3584 number of farms reported by the Dairy Farmers of Ontario, 2018. (Milk Production by the numbers.)

[13] CDIC, 2020a,2020d

Figure 1.5. 2018 Dairy Production by Province for Milk, Cheese, Cream and Yogurt (Jan-July)



Source(s): Monthly Dairy Factory Production and Stocks Survey (3430), Monthly Inventory Statement of Butter and Cheese (3431), and Milk Sold Off Farms and Cash Receipts from the Sale of Milk (3432).

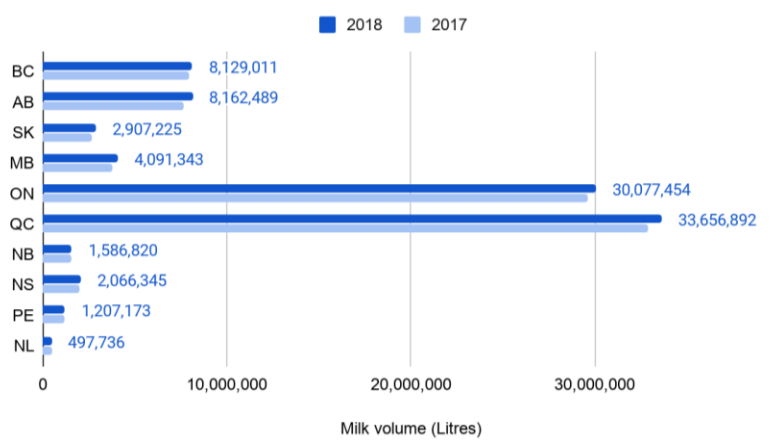
Source: StatCan, 2018

Table 1.1Share of national production, selected dairy products, 2018 (year to date), %

	Quebec	Ontario	All other provinces
Milk	24.72	38.04	37.24
Cream	14.96	48.05	37.00
Cheese	49.20	33.73	17.07
Yogurt	77.31	17.79	4.90

Source: StatCan, 2018

Figure 1.6. Total Milk Production in Canada by Province, 2017-2018



Source: CDIC, 2020d. Report D081

4. Canadian herd size structure

The Canadian dairy industry resembles the European farm profile and the north-eastern states in the US, like Wisconsin and New York, where herd size is 134 cows per herd and farm operations are not as big or as many as those in the western US and Oceania, whose average herd size is over 1000 head.[14] The larger American farms, in turn, allow producers to take advantage of economies of scale: Costs of production in Canada are 16 percent higher than in the US and "even the largest Canadian producers have 13 percent higher costs than the average American producer" (Tack, 2017).[15] Although the Canadian dairy sector has "agriculture's lowest operating expense ratio on a cash basis at 0.73, in comparison to overall agriculture at 0.83" (Tack, 2017), producers are limited by production quota limits and import restrictions from further expanding their operations. Simultaneously, while the annual milk yield per cow has been steadily increasing since 2000, the growth trend is in stark contrast to the shrinking number of farms (CDIC 2020b; 2020d).

Despite observing an increasing sum of revenue and average milk liters produced per cow over the decades, the number of farms and herd sizes in Canada have consistently diminished from the previous 1970s values[16]. On a national level, the number of dairy cows recorded in 2017 was 956 900 head, or merely 41.7 percent of 1970's total of 2 295 000 cattle head (CDIC, 2017a)[17]. Similarly, the number of farms shrunk substantially by a whopping 91.1 percent, from 122 914 in 1970 (CDIC, 2017a) to 10 951 in 2017, and to 10 679 by 2018 (CDIC, 2018). As Canadian dairy producers face a changing export flow from foreign dairy products and an insufficient amount and expensive quota units to expand their production, their operations face an ever-increasing pressure from downward price trends in the market and the need to maintain or improve their bottom-line profits. While some business analysts maintain that Canadian farmers simply "cannot win a race to condense margins" (Tack, 2017) under the current system, it is indeed in this gap between production costs and market prices where innovative production strategies can provide the conditions to remain profitable and competitive.

[14] PLQ, 2020; Edwards, 2018.
[15] While Canada's dairy farms totalled 10 951 in 2017 and 10 679 by 2018 (CDIC, 2020b), the US dairy sector had 41 819 farms in 2016, and 37 468 by 2018 (Natzke, 2019)
[16] On August 1st, 1970, Canada had 122 914 farms with shipments of milk registered. By August 1st of 2018, the number of farms registered shrunk to 10 679.(CDIC, 2020b)
[17] 2018 recorded 972 200 milking cows by January 1st, (CDIC, 2020a).

D. PROBLEM STATEMENT

Farming is not a mere source of income but it provides a sense of identity for producers and their families. Since their identity and lifestyle revolves around their operation systems, it is not only for sound business reasons that farmers want to remain profitable, but it is also in their best interest.

In a time when consumers are more conscious of carbon footprints and dietary choices, investing in energy-efficient technologies and more efficient cow progenies holds the promise to cut down production costs for farmers as well as reduce the carbon footprint of dairy production. In an increasingly consumer-driven world, securing a herd's competitive advantage within the limitations of quota production levels will hinge on finding avenues that secure the superior performance of Canadian cattle.

Sire selection is of key importance in dairy operations as it determines the entire herd composition and thus the system's maximum production and profit potential for the next production cycles. By focusing on semen transactions across the years of 1995 to 2016, this study aims to uncover the decision-making behavior of producers when selecting a bull's semen to create their new herd progeny. While there is an increasing trend observed in the Canadian milk production volumes against an ever-decreasing herd size, the econometric data examining what traits may be contributing to this trend is lacking. This study seeks to address this very gap in the literature: Through the use of semen purchasing data over the past decade, our econometric modelling looks to identify the key attributes that farmers target when making their sire selection decisions and confirm if these correspond to those linked to the genomically-innovated genes or to the pricing of the milk component schedule. Moreover, this analysis will assess if the purchasing data supports a change in attribute preferences over time along with the introduction of genomic information data, as stressed by the Canadian Dairy Network. Lastly, this study's econometric estimations will be compared against the weighted indices made to help farmers in their breeding decisions to assess if the composite set of attributes included and their contribution to each index is in line with what is revealed through the market behaviour.

Ultimately, the study's results will seek to complete the picture by reconciling the tangible, monetary values producers confer to a sire's proof attributes, back to the genomic efforts. The findings of this study can help the bottom line of key industry players, such as producers, breeders, artificial insemination companies and processors, by laying out the preference framework that Canadian farmers uphold during their sire selection. More than a contribution to the literature on farmer behaviour or the dynamics of the Canadian dairy sector, this study can provide policymakers and industry participants with a basis on attribute preferences from which to build policies that promote the uptake of genetic innovation in sire selection or to create incentives along the production chain that would support the selection of those sires with genes facilitating more efficient production. The main aim of this economic analysis is, therefore, to further define the link existing between the bull attributes and their associated monetary value to producers using multi-series, market data over time in econometric modelling.

E. STUDY SCOPE AND OBJECTIVES

This study will delve into a comparison of dairy cattle producers' decision-making strategies in relation to breeding choices. More specifically, this research will assess the reasoning behind a farmer's choice of semen for AI for their operation. To obtain the implicit value of genomic technologies embedded in the sale prices of Holstein semen doses, hedonic price functions will be employed to model bull semen transactions.

The hedonic pricing model allows researchers to uncover the values that farmers confer on each bull trait by relating these traits directly to the selling price of the semen samples in the market (Richards and Jeffrey, 1996). The selling price of the semen sample then becomes a function of the individual attributes that a semen provides as a collective unit, and the individual trait values will be associated with the importance farmers give to these attributes when deciding on the genetic makeup of their future dairy herd (Richards and Jeffrey, 1996).

Efforts to understand farmers' decisions can provide valuable information on the benefits of these technologies to the bottom line of producers, as well as the impacts on society's well-being, the effect of consumer perceptions and farmers' adoption behaviors. Understanding these effects can thus provide policymakers with tangible data to elaborate incentives towards the adoption and advancement of genomic traits, training materials and adjust environmental impact forecasts or update trade policies, for instance. We must, however, highlight the fact that these results do not set out a one-for-all path, but instead provide managers and policymakers some insight on the net economic benefits of genomics when they make the ultimate decision in regards to this technology adoption.

F. ORGANIZATION OF THESIS

The following chapter contains a literature review of the previous contributions in choice behaviour and related studies on farmer breeding decision-making. Key concepts and more background information in regards to the existing industry conditions faced by Canadian farmers, as well as the main methods to identify and select for key bull traits are thus explained in **Chapter 2**. Readers can also find an overview of the main objectives sought to be resolved with the framing of this study's economic problem. The details on the data collection, its sourcing and compounding, as well as an overview of the data's descriptive statistics is found in **Chapter 3**. Further, the econometric methods used to analyze the dataset are also explained. Successively, the results and discussion are presented in **Chapter 4**. Finally, the potential impacts and implications of the analytical results as well as their limitations, the constraints of the database and the potential extensions for future research are discussed in **Chapter 5**.

Chapter 2 . LITERATURE REVIEW

A. OUTLINE OF CHAPTER

The objectives of this study, as delineated in the previous chapter, center around studying the variation in the ranking structure of bull traits during semen purchasing decisions after the increased use of genomics in 2008. In order to assess if there are any observable changes, this thesis will evaluate the trends in traits of bulls being purchased from historical data published by Holstein Canada (1995, 2000, 2005 and 2008) and by extracting the value for those key traits from real-market transaction data in the Canadian semen market between 2008 and 2016. The second objective is thus to build a hedonic price model that can identify the monetary values conferred to each key bull trait from the semen sample prices recorded for Canadian transactions between 2008 and 2016. Lastly, this thesis also seeks to compare the preference ordering of the key traits as revealed from econometric analysis with the weights assigned to them in the main selection index of Canada, the Lifetime Profit (Performance) Index (LPI).

This section will describe the elicitation methods used by economists to identify individual attributes' values, from general identification in the literature to producer factors influencing their breeding decisions. Supporting literature will take examples from different industries, but mainly focus on dairy applications. Following firm theory, this study works under the assumption that all producers prioritize the attributes that will yield the greatest economic profit to them. Consequently, previous quantitative and qualitative models used to uncover the characteristic relative ranking for breeding decisions and their associated monetary values are discussed. Ultimately, the focus of this overview is to extract the value that farmers assign to genomically-enhanced traits. This literature overview will thus end with a summary of studies pertaining to producers' willingness to adopt innovations in breeding and the contribution of the present study to the Canadian dairy and agriculture sector, as well as the public at large.

B. MODELLING BEHAVIOUR FROM FIRM THEORY: THE CASE FOR PROFIT MAXIMIZATION/ ECONOMIC EFFICIENCY IN A PERFECTLY COMPETITIVE MARKET

Agriculture is the one industry where nature and profits are directly linked together. As stewards of the land, farmers take pride in procuring for their family and their communities through the product of their fields. Further than mere profits, it is the connection to the land, the crops and the animals they raise that builds a link between producers and their job. As Heady and Jensen (1954, p.8-9) note, the final goal is achieving “a high level of living and maximum satisfaction for the family.” Nevertheless, Heady and Jensen (1954, p.8-9) also point out that profit maximization provides a means to this end. Drummond and Goodwin (2011, 3rd ed., p.52) also observe that “evidence indicates that most farmers behave as if they were attempting to maximize profits even if the farmer states it is not his or her objective.” The notion of profit maximization as the main driver for the *firm* trails back to Adam Smith, who argued that, although a firm would act out of self-interest, it would, in fact, bring about results that would benefit consumers as well (Drummond and Goodwin, 2001, 3rd ed., p.22). Starting from the basic premise of producers seeking profit maximization, then, farmers’ behavior is consistent with classical firm theory. A farmer’s decision-making process will be thus modelled following the theory of firm behaviour.

1. Perfectly Competitive Market -implications and Associated Assumptions

Starting from a perfectly competitive market baseline, we assume that the individual farmer has no power over the price of their product nor on the price of the inputs; the number of producers is so large that one individual grower cannot affect these prices and is instead a price-taker (Drummond and Goodwin, 2011, 3rd ed., p.49). Since the products are homogeneous across different growers, and no operation is big enough on its own to effect a change in prices, producers will face the challenge of allocating their limited resources - time, money and land - across the unlimited competing options that are best for their operation (Drummond and Goodwin, 2011, 3rd ed., p.13). Additionally, firms have free access in and out of the market without concerns of paying premiums for patent usage or any exogenous barriers to entry like quotas or tariffs, for instance (Heady and Jensen, 1954, p.16). No external forces will play a role in determining prices, other than the interactions of consumers and producers in the market. In other words, firm theory aligns the neoclassical economics’ allusion to the invisible hand of the market[18]. Finally, we assume that there is perfect information among producers and consumers, such that farm managers will have perfect, accurate knowledge of market prices and forecasted yields (Heady and Jensen, 1954, p.11).

Heady and Jensen (1954, pp. 259-60) further highlight the three farm management principles that drive farmers' resource allocation decisions, "(1) the principle of diminishing returns, (2) the principle of opportunity costs - always using resources where their added or marginal return is greatest, (3) the principle of substitution." More precisely, production economics theory assumes that farmers aim to attain economic efficiency. Economic efficiency "refers to the combination of inputs that maximize individual or social objectives" and it is met under two conditions; the *necessary condition*[19] and the *sufficient condition*[20] (Doll and Orazem, 1978, 2nd ed., p.61). Ultimately, microeconomic theory states that rational firms will seek to attain maximum profits[21]. This entails obtaining the largest marginal returns, in terms of their resource endowment, from the difference between marginal revenues and marginal input costs (Drummond and Goodwin, 2011, 3rd ed., p. 17, 61, 67-69).

2. Supply Management: Adjusting for the Canadian Context

In Canada, certain agricultural commodities, such as eggs, broilers, turkeys and dairy products, are produced and sold under a supply management system. In an effort to support Canadian producers from drastic price fluctuations, the Task Force on Agriculture of 1970 suggested that supply management marketing boards be established in these industries (Davey, 2004). This government-mandated program was instituted in 1971 to respond to price instability specifically on the industries of these perishable, non-storable goods because of their large domestic markets, small to null export markets, and highly inelastic demands[22] (Davey, 2004). Namely, these policies uphold the three pillars

[18] The adjustment that occurs until the markets reach a stable equilibrium where quantity demanded will match quantity supplied (Drummond and Goodwin, 2011, 3rd ed., p. 87-88)

[19] The necessary condition relates to the physical relationship between inputs and output, where elasticity of production (ε_p) is equal or greater than zero and equal or less than one $\varepsilon_p = [0,1]$. No more goods can be produced at an established input level, and the amount of inputs required cannot be reduced any further to produce that level of output.(Doll and Orazem, 1978, 2nd ed., p.61).

[20] The sufficient condition, also called a choice indicator, is a measurement of "individual or social goals and values" (Doll and Orazem, 1978, 2nd ed., p.62) where a decision-maker evaluates his input use based on whether or not his personal goals are met (e.g. profit maximization per acre of land, yield maximization per acre of land).

[21] "basic profit-maximizing criterion for the firm is to use the variable input at that level for which the value of the marginal product is equal to the marginal factor cost" (Drummond and Goodwin, 2011, 3rd ed., p.91).

[22] Davey (2004) reported elasticity of demand for milk values ranging between -0.5 and -0.8 and highlighted fluid milk standing on the -0.8 spectrum as it was most inelastic, owing to factors such as its perishable nature, non-storability and likely prohibitive transportation costs from abroad.

of fair producer pricing, production discipline and import management (Dairy Farmers of Canada (DFC), 2018).

Each dairy year[23], the Canadian Dairy Commission (CDC), a Crown corporation, will forecast the domestic demand for industrial milk and manage the quota to each producer (Davey, 2004).

Supply management does not comply with Pareto principle, such that society as a whole experiences losses in efficiency (Davey, 2004). Schmitz et al.'s (2002; in Davey, 2004, p. 39) study confirmed this empirically, when results showed that quota levels in the Canadian dairy sector were not set at the unrestricted "profit maximizing point." Davey (2004) further supported this, asserting that the size of Canadian dairy farms were restricted by the quota levels; forced producers to operate on a higher portion of the cost curve, different from economy of scale production levels.

In economic terms, the net effect of policies such as supply management can move these industries away from perfectly competitive conditions and can result in economic losses (Schmitz, 1983). Nevertheless, producers also encounter some disadvantages in their costs of production. While the quality of the product is not necessarily compromised, the 'average' units of milk per farm are influenced by the production quota purchased by the farmer, shares that are controlled extraneously from each dairy operator and thus result in changes to the total costs of production[24] (Davey, 2004).

C. IDENTIFYING THE KEY ATTRIBUTES USED BY PRODUCERS DURING BREEDING DECISIONS: ELICITATION METHODS IN THE LITERATURE

The correct identification of the crucial attributes considered during breeding selection decisions by producers is of vital importance to breeders, dairy processors, government offices like milk marketing boards, extension services and other key players in this industry. The choice of sire can set up the ceiling of potential yield production of a herd for over a decade, let alone the expected profit margins and implicit costs like disease treatment and replacement costs. This section delves into the rationale that farmers and key players in the dairy industry have taken to identify the key traits for securing a profitable herd. In addition, the specific scenario in the Canadian dairy context is described using examples from the literature and the industry experts,

[23] In Canada, a dairy year runs from August 1st to July 31st

[24] For cases when their quota size was not initially high enough or they lack resources or opportunities to purchase further quota shares (Davey, 2004).

paying particular emphasis in the main selection index, the Lifetime Profit (Performance) Index (LPI). The evolution of its calculation since its inception in 1991 as well as the issues raised regarding the reliability of this composite index are also described. Consequently, this overview will move to elaborate on the available econometric methods to elicit the most important attributes farmers prioritize in the breeding selection decision and conclude with a thorough description of the hedonic price model, our method of choice for this study.

1. Managing Breeding: Prioritizing attributes to pass on

Choosing a bull is one of the most impactful decisions in the makeup and productivity of a dairy operation: A single cow can only give birth to one calf every year, whereas one bull alone can sire 25 or more calves in a season (Barham, 2015). Cows will usually give birth to new calves every 14 months, starting at 2 to 3 years of age (Track, 2017), and from these, a farmer will choose replacement heifers to upgrade and maintain the herd[25]. The effect of a sire selection on a cow herd does not merely affect the operation in one season, but it has "a lasting impact upwards of 15 years on a cow herd" (Drovers, 2015) since the cows in the herd and their progeny used for replacements will be affected. Therefore, selecting the right sire for their operation is of vital importance, as approximately "three-quarters of the genetic flow of the cow herd is driven by sire selection", according to Kansas State University researcher, Bob Weaber[26] (Orrock, 2015).

1.1Traits to improve

In the past, farmers used to rely on phenotypic data through recorded performance indicators and body condition as well as "a lot of *eye-ball* in the selection process" (Rethorst, 2015, p.8). The Record of Improvement system was instituted in Canada, assisted by the federal government in 1905 and supervised by the Livestock Division to monitor milk production (Nicholson, 2002). Legislation for keeping lactation records and ensuring breed improvement came through the Canadian Record of Performance (ROP); farmers who registered their cows under this program and tested their milk production gained permission to sell their registered bulls (Nicholson, 2002). These records were computerized and the proven bulls were finally linked to their sired dams in 1972 under the National Identification Program (Nicholson, 2002).

[25] On average, the cost of raising an additional replacement heifer is $2,500 CDN (Hunt, 2019b). However, Hunt (2019b) cautions that replacements bred from a lower producing cow will only offset about $1800 CDN of the cost from its first lactation cycle.

[26] Naturally, a bull to cow breeding ratio is 1 to 25 or 30 (Swigert, 2015, p.32) and with AI, that number could extend to the entire herd.

Currently, farmers keep track records of performance and production values of their operation and assess their herd for improvements that they would like to bring to their farm through the next replacement decisions (Hunt, 2019b). In addition, the Canadian Holstein association and the Canadian Dairy Network[27] (CDN) provide nationwide, publicly accessible information on registered sires across the country with relative grading scores for production and type-related traits[28], usually with Estimated Breeding Values[29] (EBVs). The attributes reported by the CDN are chosen based on the economic value conferred by farmers, and these evolve as their appraisal of certain traits increased (Boettcher and Van Doormaal, 1999; Van Doormaal et al., 2001). Consideration of specific traits to focus on for selection decisions usually hold several qualities in common; they have a marketable value alone or its improvement will result in lower production costs (1); their measurement and recording is affordable and performed regularly (3); there is a high genetic correlation with traits that are economically valuable (4) (Shook, 1989). As a result, every bull will have scores on traits associated to their daughters' production averages for milk volume, fat and protein content, milking speed, herd life and somatic cell score but also qualitative traits like calving ease, lactation persistency, and milking temperament (Boettcher and Van Doormaal, 1999). As the number of traits and the level of detail about traits increase over time, most farmers narrow it down to a select number of key attributes (Richards and Jeffrey, 1996).

Ultimately, farmers aim to "target an acceptable combination of traits that complement the strengths and weaknesses of the cow herd and match markets" (Barham, 2015). More specifically, industry experts find that Canadian dairy farmers looked to increase the production rates of milk per cow and increase the ease, efficiency and longevity of their operations by selecting sires with proven progeny records for higher milk production yields as well as higher butterfat and protein

[27] The CDC serves as a federal government board to the Canadian Milk Supply Management Committee (CMSMC)(DFC, 2018). The CDC is in charge of setting supply controls, such as the production levels for industrial milk; the marketing orders, like the domestic prices for dairy products; and determining and upholding quota shares and rights (Schmitz, 1983).

[28] *Type traits* describe "skeletal characteristics of an animal" and "are moderately to strongly genetically correlated with a range of other performance traits in cattle including feed intake, reproduction traits and carcass merit" (Doyle et al., 2020, p.1). In Canada, the CDN collects scores for a total of 27 different type-related traits, but publishes genetic evaluations with 21 of these, which include attributes like conformation, dairy character, frame/capacity, feet and legs and mammary system (see **Appendix 3** for a comprehensive list of these traits) (CDN, 2000).

[29] Estimated Breeding Values (EBVs) are "a value which expresses the difference (+ or -) between an individual animal and the herd or breed benchmark to which the animal is being compared. EBVs are reported in terms of actual product e.g. days, kg of weight or mm of fat depth, etc." (The Cattle Site, 2011).

percentage, and positive reports for ease of calving and daughter fertility, for instance (Harris, 2019).

Using experience in the dairy industry and discussions with dairy representatives, Richards and Jeffrey considered the attributes available in proof data and limited their analysis to nine main traits; milk volume, protein and fat content, conformation, body capacity, quality for feet & legs, as well as mammary system, and number of daughters. Additional empirical results in the literature indeed support that specific traits are outstanding in semen selection; Martin-Collado et al.'s study of Australian dairy farmers (2015) found that, across all groups, producers favored improvements on traits related to mastitis, longevity and fertility the most, while they cared the least for milking speed, lactation persistency and cow live weight. In addition, the most important traits for selecting a bull, on average, were semen fertility and the EBV mark for production and management traits (Martin-Collado et al., 2015). As Boettcher and Van Doormaal (1999, p.1) explained, however, most of them now look beyond the milk production scores when choosing the optimal sire for their operation: "They realise functional traits such as longevity and health must also be considered in selection, because these traits have a direct impact on total economic merit and may be unfavorably genetically correlated with yield."

In addition to these separate attribute values, farmers can also compare sires using the composite average indices made by dairy associations. Often, farmers will refer to a publication to get reliable scores on multiple attributes, called proofs (Richards and Jeffrey, 1996), or seek out live sales. The merit of these indices lies in the fact that they "are based on multiple traits weighted for economic importance, heritability (the proportion of the differences among cattle that is transmitted to their offspring) and genetic associations among traits" (Barham, 2015). Assessing the level to which the Canadian selection index, the LPI, can accurately summarize farmers' attribute enhancement priorities while also providing guidance on profitable bull selection is thus our third and final objective in this study.

1.2 Weighted-average indicators in Canada: The Lifetime Profit Index (LPI)

In Canada, the CDN carries on the task of calculating and publishing all the genetic evaluations for dairy cattle in the country (Boettcher, Van Doormaal, 1999). Canadian farmers have a multitude of indices to choose from when picking a sire to produce a new herd, such as the Lifetime Profit (Performance) Index (LPI) to further aid farmers in making successful and profitable breeding choices (Hunt, 2019b). The Lifetime Profit Index (LPI) was introduced in 1991 as an indicator of the genetic advantages of a bull, cow or heifer over another in terms of breeding for profitable dairy herds (Van Doormaal, 2013). The main objective was to provide farmers with a single measure that farmers could reference when trying to make breeding decisions such that a higher LPI would signal more profitable progeny over their lifetime relative to the lesser-ranking animals (Van Doormaal, 2013).

This composite index was built from a weighted average of different attributes identified as being of importance to farmers and key to their operation's profit. LPI rankings are constructed annually for each breed using a composite weighted-average of several attributes like *Fat Yield*(F); *Protein Yield* (P); *Conformation* (Conf); *Frame/Capacity*; *Feet And Legs* and; *Mammary System* (MS). The different characteristics are divided by each trait's standard deviation (s.d.) in order to make them comparable and allow for the LPI indicator to surmise them into one single unit-less value (Van Doormaal, 2013).

1995 Formula (Holstein Canada, 1995):

$$LPI = 63 \text{ Fat} + 8 \text{ Protein} + 43 \text{ Final Class} + 4 \text{ Mamm Syst} + 2 \text{ FeetLegs} + \text{Capacity}$$

2000 Formula (Holstein Canada, 2000):

$$LPI = 8\left(6\left(2\left(\frac{F-avg}{sd}\right)+9\left(\frac{P-avg}{sd}\right)\right)+4\left(\frac{CONF}{sd}+\frac{FrC}{sd}+4\,\frac{FL}{sd}+5\,\frac{MS}{sd}\right)*cf\right)$$

where F= EBV Fat, P = EBV Protein, CONF = EBV conformation, FrC= EBV Frame/Capacity, FL= EBV Feet and Legs, MS = EBV Mammary System, avg = average proof value, sd = trait standard deviation, cf = correlation factor.

2005 Formula (Holstein Canada, 2005):

$$LPI = [PRODUCTION] + [DURABILITY] + [HEALTH \,\&\, FERTILITY]$$

$$\begin{aligned} LPI = &\left[54\left[5.7\left(\frac{P-avg}{sd}\right)+0.3\left(\frac{PD}{sd}\right)+3.8\left(\frac{F-avg}{sd}\right)+0.2\left(\frac{FD}{sd}\right)*cf_1\right]\right] \\ &+\left[36\left[2\left(\frac{HL-avg}{sd}\right)+4\left(\frac{MS}{sd}\right)+3\left(\frac{FL}{sd}\right)+\left(\frac{FrC}{sd}\right)*cf_2\right]\right] \\ &+\left[10\left[-3.0\left(\frac{SCS-avg}{sd}\right)+1.5\left(\frac{UD}{sd}\right)+0.5\left(\frac{MSp-avg}{sd}\right)+5.0\left(\frac{DF-avg}{sd}\right)*cf_3\right]\right] \end{aligned}$$

where F= EBV Fat, P = EBV Protein, PD= Protein deviation, FD= Fat deviation, HL = EBV Herd Life, MS = EBV Mammary System, FL= EBV Feet and Legs, FrC= EBV Frame/Capacity, SCS= EBV somatic cell score, UD= EBV udder depth, MSp= EBV milking speed, DF= EVB daughter fertility, avg = average proof value, sd = trait standard deviation, cf = correlation factor.

2008 Formula (Holstein Canada, 2008):

$$LPI = [PRODUCTION] + [DURABILITY] + [HEALTH \;\&\; FERTILITY]$$

$$\begin{aligned} LPI = \Bigg[51\ \left[5.7\left(\frac{P-avg}{sd}\right) + 0.3\left(\frac{PD}{sd}\right) + 3.8\ \left(\frac{F-avg}{sd}\right) + 0.2\left(\frac{FD}{sd}\right) * cf_1\right]\Bigg] \\ + \Bigg[34\ \left[2\left(\frac{HL-avg}{sd}\right) + 4\left(\frac{MS}{sd}\right) + 3\ \left(\frac{FL}{sd}\right) + 1\left(\frac{DS}{sd}\right) * cf_2\right]\Bigg] \\ + \ \Bigg[15\ \left[-2.0\left(\frac{SCS-avg}{sd}\right) + 1.0\left(\frac{UD}{sd}\right) + 0.3\ \left(\frac{MSp-avg}{sd}\right) + 6.7\left(\frac{DF-avg}{sd}\right) * cf_3\right]\Bigg] \end{aligned}$$

where F= EBV Fat, P = EBV Protein, PD= Protein deviation, FD= Fat deviation, HL = EBV Herd Life, MS = EBV Mammary System, FL= EBV Feet and Legs, DS= EBV Dairy Strength, SCS= EBV somatic cell score, UD= EBV udder depth, MSp= EBV milking speed, DF= EBV daughter fertility, avg = average proof value, sd = trait standard deviation, cf = correlation factor.

General LPI Formula (Holstein Canada, 2008):

$$\mathbf{LPI} = \left\{ \begin{array}{c}\textbf{Production}\\\textbf{Component}\\\textbf{x Emphasis}\\\textbf{x Factor}\end{array} + \begin{array}{c}\textbf{Durability}\\\textbf{Component}\\\textbf{x Emphasis}\\\textbf{x Factor}\end{array} + \begin{array}{c}\textbf{Health \&}\\\textbf{Fertility}\\\textbf{Component}\\\textbf{x Emphasis}\\\textbf{x Factor}\end{array} \right\} + \textbf{Constant}$$

After its original introduction in 1991, the CDN adjusted the LPI formula using Gibson et al.'s (1992) findings, and went on to use it until 2013, when the network re-evaluated its accuracy with industry and geneticists, and moved towards a greater revision to simplify the financial implications of LPI points; "Every point increase in the average LPI of a herd now translates to a parallel increase of one dollar profit per cow per year for the lifetime of the daughter" (Van Doormaal, 2013). In August 2014, the new index on Mastitis Resistance was added into the Health and Fertility component of the LPI formula, while the direct standard deviations from fat and protein were removed from the Production component. A year later, in August 2015, the weights of the main trait categories for the LPI changed from 51 percent for Production traits, 34 percent for Durability traits, and 15 percent for Health and Fertility traits, to 40, 40 and 20 percent, respectively. The index would heavily select on conformation, fat and protein (Beavers and Van Doormaal, 2015). **Table 2.1** shows the changes in the weights of the general trait categories of the LPI over time from it's first publication, 1991, to 2018.

While the literature recognizes that this composite index did aid as a signal to increase a herd's genetic merit overall (Beavers, 2017), a growing concern that the LPI was not reflecting farmers' interests but was “a synthetic profitability ranking of bulls” prevailed (Richards and Jeffrey, 1996, p.262). Richards and Jeffrey (1996, p.260), for instance, performed a comparative analysis between the LPI formula and a cross-sectional estimation of the hedonic pricing model and their results suggested the latter “provides a better explanation of semen than does the LPI.” However, the analysis was not repeated or extended past the 1995 results. Moreover, as Hunt (2016) explains, “one size does not fit all. Not every new genetic index, total merit or individual trait, will assist a breeder in breeding an ever more profitable herd.” Although the CDN (2014) explained that the LPI scores do not translate directly to profit gains, this index is the leading indicator on dairy performance in Canada. Therefore, it will be interesting to evaluate whether current hedonic estimations would parallel the change in trait preference that the LPI category weights show over time or not, given its long-standing use as a reference source in breeding decision-making.

Table 2.1 LPI weight values over time, 1991-2016

	1991-2000	2001-2004	2005-2007	2008-2015	2016-2018
Production	60	56	54	51	40
Conformation/ Durability	40	38	36	34	40
Health/ Fertility	0	5	10	15	20

Issues raised on the reliability of the LPI

Although the Canadian Dairy Network works with breeders and stakeholders to create the LPI measure and bases its measurements on Canadian farm’s average expenses and returns, there are several concerns raised in the literature in regards to their representability and accuracy (Hunt, 2013). One concern brought forward is the extent to which the LPI index is applicable across the different provinces since the costs and returns employed to estimate the different weights in the LPI function are based largely on five-lactation periods from Ontario cows (Richards and Jeffrey, 1996). Similarly, there is an additional bias stemming from the five year production period estimated, as it calculates the same trait longevity for all the offspring, regardless of differences in bull characteristics (Richards and Jeffrey, 1996). In addition, the focus on average costs from changes in milk production does not directly translate to the marginal cost derived solely from investing in genetic improvements of a herd (Richards and Jeffrey, 1996). Finally, Richards and Jeffrey (1996) point out that the LPI index works under the assumption of fixed production despite the ever-changing technology component of dairy operations, such that the measurement does not work under the assumption of optimal economic behavior. This fact was further supported with Beavers and Van Doormaal's (2015) advisory statement on how the "lifetime profit can be defined differently from farm to farm, depending on the sources of revenue and associated expenses."

Furthermore, Richards and Jeffrey's (1996) comparative analysis on the forecasting power of the bull characteristics with a hedonic price function against the LPI index, and concluded that the hedonic model surpassed the LPI's highly significant predictive power at a lower cost and through a more straightforward and applicable manner. This finding supports the claim that weighted indices are redundant if a hedonic price function is established accurately (see Richards and Jeffrey, 1996 for more details on LPI concerns). By estimating a new hedonic price function, this thesis pursues three main objectives: (1) to analyze any observable changes in the average valuation of the main bull proof characteristics for cattle breeders; (2) to further build the case for this method's credibility as a valuable tool for producers and AI companies for reaching their breeding objectives and (3) to contrast the weighting of the key traits in the LPI formula with the results obtained from the hedonic estimation across time.

The objective of this present study is thus, to analyze how the valuation uncovered from semen transactions in the Canadian Holstein market compares to the weights highlighted in the LPI. Indications of a discrepancy between perceived valuation of sire attributes by farmers through our analysis and the most conducive attributes for realized profits according to the CDN findings could suggest that there is a disconnect between farmer's sire selection criteria and their herd's actual performance. Implications from our study could thus lead to policies and industry adjustments to create extension programs or incentives to change the attribute preference structure for Canadian dairy producers.

2. Quantitative and Qualitative Analysis: Modelling Approaches

In broad terms, Roosen, et al. (2005) summarized the available approaches to extract the economic value of farm animal genetic resources (AnGR) as models that use revealed, market-available data, and those that elicit information from constructed surveys (i.e. stated choice data). While all alternatives make use of "econometric or mathematical programming approaches to analyse the data" (Roosen et al., 2005, p. 226), the methodology and underlying economic theory they appeal to differs. On the one hand, primal approaches focus on the profit function and perform partial budget analyses, farm simulation models or research and development models (Roosen et al., 2005). Alternatively, dual approaches deal with the production factors that stem from the derived demand function. These include; estimating the demand and supply equations; using a hedonic value function or turning to stated preference alternatives (i.e. contingent valuation (CV), conjoint analysis (CA), or choice experiments (CE)).

2.1 Primal approaches: Production function based models

Model	Description	Limitations	Sample studies
a) Partial budgeting	• Compares the costs and revenues among two production activities and reconciles the difference in profits to obtain the value of a resource or breed above another one in "pure accounting" terms (Roosen et al., 2005, p.221). • Approach is closely similar to the "economic weights in genetic improvement programmes based on Hazel's (1943) seminal work." (Roosen et al., 2005, p.222) • Relatively easy to carry out using accounting sheets to calculate the overall performance,	• **Static method:** Assumes that input use remains constant, so it "models farmers' choices as artificially inflexible" (Roosen et al., 2005, p.221). • Fails to reflect potential changes in production technology and markets. Unable to forecast the absolute profitability of the farm operation. • Can only assess a minor change, as opposed to a "major reorganization" (Dillon and Hardaker, 1980, p.81)	Takele (2019)
b) Cost of Production (CoP)	• Estimation of all of the different costs involved in running the farm operation for one production year/cycle (Takele, 2019). • Elements in calculation include: (1) Direct operating costs - associated solely on the production requirements of the good at hand; (2) Fixed/ ownership costs - the costs the farm will incur, regardless of	• Calculations might not be comparable across different farms, regions or countries: Estimation procedures can be different -like using replacement or historical basis for depreciation or including versus omitting opportunity costs-, "and may, in fact, be	Groenendaal et al. (2004), Province of Manitoba, (2019).

	being in business or not (Takele, 2019). • Although it requires careful recording of all the different components involved in the farm operation, it uses very limited sales data (Hagerman et al., 2017).	responsible for the different levels of cost reported" (Ahearn et al., 1990, p.1290). • Limited use of CoP data as indicators for planning since estimation is built upon average costs, as opposed to the marginal costs "underlying the industry supply curve, the relevant concept" (Ahearn et al., 1990, p.1284).	
c) Farm Simulation Models	• Consider substitution effects of input and output choices as well as market price changes (via producer demand elasticities) and allow for all farm activities to be considered in the model/program (Roosen et al., 2005). • Economic values for genetic traits are estimated from running these farm-level simulations by specifying the precise technical relationships held between the inputs in the production process and the outputs.	Requires highly detailed information on technical coefficients and an advanced knowledge to link prices in the production function to genetic traits (Roosen et al., 2015).	Beukes et al. (2010), Valergakis et al. (2007)
d) Vector Error Correction Modelling (VECM)	• Used for multivariate time-series that are non-stationary and hold a cointegrating relationship among each other I (1) (Adkins, 2019). • A type of Vector Autoregressive model (VAR) that accommodates for the presence of cointegration among the non-stationary, time-series variables via a vector error correction term (Hauser, 2019).	• The high level of cointegration and additional methodological requirements to bypass nonstationarity in the time-series still poses challenges towards obtaining unbiased results (Hagerman et al., 2017).	Hagerman et al. (2017)
e) Models for Research and Development (R&D)	• Compare the funds invested into the project to the economic gains from the enhanced genetic stock to evaluate an R&D project's efficiency. Can be done ex ante through simulation models or ex post with observed data (Roosen et al., 2005). • Results can be used in "benefit- cost analyses of research on animal genetic traits." (Roosen et al., 2005, p.221)	• Availability of data detailing the precise values and extent of the possible research results, as well as the "links between AnGR and phenotypic trait development" is challenging (Roosen et al., 2005, p.222). • Potential biases can arise from an ex post evaluation of new technology adoption, namely due to endogeneity (Hailu et al., 2017).	Hailu et al. (2017), Falconi et al. (2001)

2.2 Dual Approaches: Derived demand function based models

Within the models based on the derived demand function, there are estimations that use revealed choice data from the market transaction, to estimate the demand and supply schedules, or to bring intrinsic values of a market good to the surface employing a hedonic price model, and there are estimations that use stated choice data, namely contingent valuation models, conjoint analysis and choice experiments (Roosen et al., 2005).

	Description	Limitations	Sample studies
a) *Econometric Demand and Supply Schedule Estimations*	Demand and supply equations are built from the available market prices and individual purchase data and later linked to phenotypic traits and AnGR data (Roosen et al., 2005).	Maintaining the production link between the farm and the consumer to directly associate a particular breed to the good, like milk, meat or wool to its source of origin can be challenging, as they will be usually bulked with others and the relationship will be lost (Roosen et al., 2005).	Scarpa, (1999)
b) *Hedonic Price Model*	Built on consumer theory as explained by Lancaster (1966), where the utility of consumers is a function of the attributes conveyed in the good that they purchase. The value of the good is a result of the collection of attributes that it carries. Two methods available: (1) analyze the individual value of “alternative characteristics” of market goods from their selling value, like fat content in milk or vitamins and other credence values, or; (2) Associate the attributes that are valuable to farmers to the production process by relating them to the overall animal market prices (Mendelsohn, 1999).	A challenge to implementing revealed choice data approaches, is the lack of observable market data to carry on the analysis. Roosen et al. (2005, p. 221) state, “(m)arket data on livestock resources is normally collected at the species level and not at the breed level”, and even when it is available, researchers can still struggle to conduct the model, as the data “might not be detailed enough or may not permit to evaluate resources that are rare and not often observed” (Roosen et al., 2005, p.223).	Walburger and Foster (1994), Richards and Jeffrey (1996)
c) *Stated choice models*	i) *Contingent Valuation (CV)* Used when revealed choice data is unavailable. Relies on survey research methods to collect information, where respondents must choose between alternative hypothetical scenarios (Roosen et al.,2005). Each scenario is associated to a price to obtain the respondents’ willingness to pay (WTP) or willingness to accept (WTA) swapping into one of	i) Vulnerable to biases in the respondent selection, either by a non-response bias from segmenting the sampling population (e.g. only specialists understand the breeding techniques and germplasm information respond), or by strategic bias, where the respondents have an incentive to influence the outcome by manipulating their survey choices (Evenson et al., 1998; Roosen et al., 2005). ii) Can only obtain the ranking of preference orders for a series	i) Adamowicz et al., (2011), Cicia et al. (2003) ii) Louviere et al., (2001), Tano et al., (2003) iii) Adamowicz et al., (1998), Scarpa et al. (2003),

	the scenarios. Plays a big role in benefit-cost analysis studies. *ii) Conjoint Analysis (CA)* Also follows Lancaster's consumer theory, and thus, also uses a multi-attribute estimation approach to obtain the contribution of each attribute to the value of the market good separately (Roosen et al, 2005). Presents respondents with different scenarios with varying level combinations of the attributes to allow for measuring the individual effect of the attributes and set a preference ranking order (Roosen et al., 2005). Widely used in benefit-cost analysis studies. *iii) Contingent Choice* *Experiments (CE)* CE builds on CA; it estimates a measure for WTP/WTA, in addition to determining a preference ranking system from the selection behaviour and the ranking of products like CA d*oes.* Cover alternative substitutes more robustly than CV surveys (will include them in the selection process among the set of alternatives)	of products and predict choices but cannot estimate WTP/WTA measures. iii) Cognitively challenging for respondents. Advanced experimental design techniques required.	

Our objectives will analyze the data available from real market transactions of semen samples in the Canadian Holstein market using a Hedonic Price Model. This model explains the prices observed in the market are a result of individual bid functions from different consumers interacting with suppliers (individual offer functions) to maximize their own utility when purchasing a trait level (q, for instance, protein yield level), subject to their own budget constraints (Grafton et al., 2004). Consequently, the latent hedonic price function is generated by the intersection of the offer curves and bid curves at a specific price and quantity level of all attributes (i.e. the level that matches the willingness to pay for consumers and the willingness to accept for suppliers) (Grafton et al., 2004). In order to carry out this econometric estimation, animal semen purchases in the formal market (i.e. price data) are needed to serve as the dependent variable, while data on genetic attributes is needed to decompose the animal's value into its individual traits as explanatory variables. The marginal effects of the individual attributes will reflect the changes in the price that are associated with each specific attribute, when everything else is held constant.

2.3 Extending on the Hedonic Price Model

This section will expand on the theoretical model in the context of trait valuation in the livestock industry. Other than the specific formulas that describe the economic principles behind this model, particular examples in the literature and the model's limitations in the empirical setting are reviewed here. The hedonic price model was chosen as a means of identifying any change in valuation of the key sire attributes before and after the increased use of genomics in 2008 because of its ability to elicit the monetary value of traits from economic transactions (Grafton et al., 2004). In addition, we seek to further analyze the predictive value of econometric methods in comparison with weighted selection indices, like the LPI, for producers and key industry players. Ultimately, as Miglior et al. (2017, p.10252) underscore, "the identification of traits that are presently important for genetic selection and those that will be essential in the future is a vital aspect of selection research."

a) Hedonic Modeling: Extracting the value of genomic innovation from bull transactions

Attribute based models, unlike the classic demand models, work under the assumption that attributes of a good, such as the number of bedrooms in a house, or the pure breed trait in a bull, also yield utility to purchasers and thus, also contribute to the overall price of that good[30]. The function itself represents the combined decision of sellers and buyers to engage in a transaction, subject to the buyer's budget and the seller's level of technology[31]. More specifically, a hedonic model analyzes the market-clearing price and decomposes prices into several characteristics[32].This is particularly helpful when trying to obtain implicit values of a trait in products that are very slightly differentiated based on these attributes[33]. These have been used extensively in wage relationships to study the WTP for risk reduction[31]. In a similar fashion, farmers' willingness to pay (WTP) for these attributes is embedded in the purchase price for bulls and semen vials. The aim of this application is to extract the value of those attributes of interest from the overall good bundle.

[30] Bockstael and McConnell, 2007
[31] Grafton et al, 2004
[32] Bockstael and McConnell, 2007
[33] Freeman et al., 2014, 3rd ed.

More specifically, Mitchell and Peel (2016) used hedonic price modelling to analyze several cow attributes in Oklahoma cow-calf pair value auctions for 1993 data and found various factors like age, breed, size and gestation status were highly significant (Hagerman et al., 2017). Moreover, they found significant, positive effects on cow prices for younger, heavier, high-quality and later-gestating cows (Mitchell and Peel, 2016). Similarly, Hagerman et al. (2017) used data from Oklahoma cows between 2000 and 2015 in a hedonic price model to forecast market prices for the year 2016. Their application of hedonics revealed the intrinsic values of explanatory variables like age, weight, gestation months, hide colour, quality (high, above average, below average, low), cow lot type (cows, heifers, cow-calf pairs) and market region (west region) in the sale price of cows. Age, quality, breed type, lot type were highlighted as most significant, with lot type being “the most preferential” (Hagerman et al., 2017, p.10).

In Canada, Walburger and Foster (1994) used hedonic price modelling when extracting the implicit values of non-marketable swine attributes from boar sale prices. While all the estimates had the expected signs, it was the backfat and the loineye area traits which showed the greatest increments in marginal implicit prices from 1987-89 to 1990-91(Walburger and Foster, 1994). Overall, an interesting observation was that most attributes were significant when their degree of heritability was moderate to high, but insignificant for a trait with low heritability like the number of piglets farrowed (NF) (Walburger and Foster, 1994). In the dairy field, Richards and Jeffrey (1996) used the Hedonic price model to regress a cross-section sample of Holstein semen prices (n=694) as a function of productivity-related and type-related attributes, as well as a binary variable for the availability of the semen sample. Their results indicated that all their bull attribute covariates were significant for semen prices, with protein, fat and semen supply having the greatest marginal effect on the market value for semen vials (Richards and Jeffrey, 1996).

Similarly, this current study will make use of hedonic modelling to identify the value genomic technology has in farmers’ sire selection process through the valuation of bull traits from semen purchases. While the increase in trait identification and the improvement of measurement methods of these bull traits grow through genomics, the value of a trait in a producer’s mind may change[34].

[34] Although the pricing of different semen samples also changes due to sellers’ perceived value of the quality of the doses, this study focuses on the buyer-side of this transaction. That is, dairy producers’ semen selection process is the sole focus of the analysis.

Evidence of the value of these scores increasing their degree of credibility lies in the increasing use of younger bulls, who do not have sufficient daughter data to fully identify the key traits of interest (Boettcher, 2005; Greig, 2018). In contrast to limiting the analysis to a single year, cross-sectional analysis, this estimation will use purchase data for Holstein semen samples from the year 2008 until 2016 (n=7795) provided by Miglior (2017). Ultimately, through the use of hedonics pricing, the producers' trait selection focus will also be uncovered by the proportion of sales with type versus production traits. In addition to deepening the findings of Richards and Jeffrey (1996) in regards to dairy producer prioritization during sire selection, this current study will examine the industry's assertion that Canadian producers are switching over from being type-focused to production-focused when ranking attributes (Richards and Jeffrey,1996; Beavers and Van Doormaal 2017). No further econometric studies have been performed in this area to further support this observation nor to update it in the face of genomics being introduced in Canada. Finally, the valuation conferred by farmers to the different traits can also inform us on the accuracy of the weights that are given to the different attribute-components in the main composite index of Canada, the LPI.

b) Description of Hedonic Modeling

Overall, the hedonic price model is the result of an aggregate series of bid curves from separate individuals interacting with separate sellers in a market to maximize their own utility from the purchase of a good or service (Grafton et al., 2004). In this study, the hedonic price modelling represents the sum of different dairy producers interacting in the Canadian semen market looking to maximize their utility from their semen purchase for their particular budget constraints. This section explains the economic theory that composes the hedonic modeling functions and the general mathematical representation of the model. Specific applications and the interpretation of this model to our economic problem is explained in detail in the next chapter.

Generally, the utility optimization problem to follow is represented as;

Max. *Utility* (z, q_i) subject to $\sum p_i q_i + z \leq M$

where *p* refers to the prices of the good at hand, for any *i* number of goods; *q* represents the different attributes for the *i*th good; *z* is the numeraire, and; *M* is the income or budget constraint[35].

[35] Grafton et al., 2004

Solving for the optimal values for this equation will result in a bid function, Θ(*q*, *U*, *M*)[36], where the derivative of Θ with respect to q_i will equal the marginal rates of substitution between q_i and z[35].

$$\frac{\frac{\partial U}{\partial q_i}}{\frac{\partial U}{\partial z}} = \frac{\partial \Theta}{q_i}$$

This derivative, in turn, will represent the willingness to pay for attribute *q* at a specific level of *M* and *U*[35]. Similarly, suppliers will specify their offer function as ψ (*q*, π,τ), where *q* refers to the different attributes, π is the profit and τ is the specific technology level available)[35]. Tracing out the points where the willingness to pay for all the possible levels of q (for a given utility level) are tangent to the willingness to accept (for a given technology level), would render the Hedonic Price Function; $P= f (q_1...q_i)$[37].

Therefore, the Hedonic Price Function represents the interactions between consumers and producers of a good, as it reflects the tangencies between these bid curves and the offer curves (the supplier's counterpart)[38]. The marginal value of an attribute q_i can be obtained from differentiation with respect to q_i.

c) Limitations

Hagerman et al.'s (2017) evaluation of the hedonic price model as a forecasting tool for future beef cow prices in Oklahoma found that overall, the effect of the explanatory variables used in their model, in terms of both the direction and the magnitude, align with what was seen in previous literature. Nevertheless, although the hedonic model was best at forecasting high-quality cow prices, and was second-best among their econometric approaches for estimating average quality cows, their results showed that it consistently inflated the prices within the replacement females and the heifer sample (Hagerman et al., 2017). Similarly, Kessler et al.'s (2016) hedonic modelling of Colorado breeding bulls found performance measures like yearling weight and EPDs (Expected Progeny Differences)[39], such as weaning weight and milk production, had positive effects on bull

[36] U refers to utility
[37] Bockstael and McConnell, 2007
[38] Freeman et al., 2014, 3rd ed.
[39] A measurement used by beef cattle producers to compare one specimen to another of the same breed in terms of their genetic value. These values indicate the differences they would expect in their progeny based on genetics (Drovers, 2015).

prices while particular attributes, like lower pulmonary arterial pressure, were only sought after by Colorado ranchers due to the high altitude of the region.

These studies speak to the hurdle that stems from interpreting many econometric estimations, including the hedonic model: Knowing the extent to which these findings apply to other regions and/or countries. Hedonic models succeed in revealing the intrinsic value of attributes contributing to the perceived market price of a good or service, but it imposes the assumption that the underlying utility and price relationships will continue to hold across time and geographic area (Hagerman et al., 2017). As it is evident from their concluding remarks, both studies caution readers on the degree of reproducibility and affinity of their results under different geographic scenarios (Hagerman et al., 2017; Kessler et al., 2016). These examples in the literature, using analogous cattle markets and evaluating farmer preferences during breeding decisions, set a precedent for us to take heed of the extent of our results' application and implications for dairy farmers in Canada and other countries. Ultimately, as Hagerman et al. (2017, p.14) caution, "it is up to the individual researcher to determine the level of regional aggregation, time frame and tolerance for inaccuracy that is most appropriate for the question being asked."

Rather than approach the case of dairy producer behaviour over sire selection as a one-all scenario, researchers in this field are encouraged to remember that econometric models like hedonic pricing will only yield results over the average set of preferences in the sample, and it will not necessarily speak to the different farmer typologies or clusters happening across the different regions of Canada or other nations. The hedonic pricing application of this study embeds farmers' demand for adopting technology, and our results will reflect upon the population of farmers participating in semen purchases. Further segmentation of our data is beyond the scope of our analysis.

D. ADOPTION OF INNOVATION: FACTORS AFFECTING THE RATE OF TECHNOLOGY UPTAKE AND DIFFUSION

When examining the role that individual farmer characteristics and farm structural differences play in the adoption of artificial insemination (AI) for breeding in beef and dairy operations, Howley et al. (2012) used 15 years of qualitative data from the Irish National Farm Survey (NFS). Other researchers, in turn, relied on previous literature and prior experiences with farmers in the industry to extract the main attributes that influence the breeding decisions (Hagerman et al., 2017; Richards and Jeffrey, 1996; Walburger and Foster, 1994). This study will restrict itself to the use of hedonic modelling to uncover the economic value of sire attributes from semen transactions, but the authors do recognize that there are other factors that can play a role in the valuation structure of producers, as well as their willingness to adopt technologies selecting for less-heritable traits, and the effectiveness of their results. Other elements of relevance in the breeding selection decision worth considering when evaluating the validity of our results and the limitations of our approach are described briefly in this section.

1. Individual-specific Characteristics

Regressions of market conditions like price or demand of a good *Y* can show a correlation to traits associated with a good *Y,* when the traits are used as explanatory variables, to analyze the market behaviour of *Y* - like the level of milk supply by herd size or the amount of poultry or glyphosate demanded by season or crop variety, for instance, - where there will be a direct association between the market behaviour and the direct, measurable traits of the good at hand. Nevertheless, economists also acknowledge that the links between certain good characteristics and a market condition is not one-dimensional but instead other factors associated to the consumer or producer of the good may come into play also. This phenomenon can be seen within a wide variety of subjects, ranging from the demand for recreational park services, and the score or the wage distribution of a group sample or, in the case of this study, the semen prices of genomically-sourced bulls in Canada. Similarly, studies in Colombia on health and sanitation by Rogers (2003, 5th ed.) helped him identify certain factors curtailing adoption, such as the culture of a society or organization (aspects like belief systems, risk perception and the value and adherence to scientific data), the local environment (reinforcing homogeneity or encouraging experimentation and entrepreneurship), and individuals (authorities, legislations, opinion leaders and social networks). While regressions of the previous examples can be constructed based on characteristics of the goods, there will be *observable* traits of the decision-makers, like their disposable income level; the amount of hours invested in studying; years of experience or education, respectively, and *unobservabl*e traits, like the value they attach to nature and recreation; their innate intellectual skills or ability to adapt in the job or use technology, that can also impact the results seen in the expressed behaviour (Greene, 2012, 5th ed.; Verbeek, 2012, 4th ed.).

One of the most concrete examples can be drawn from the human capital earnings function:

> It is quite clear that, on average, people with more education have higher wages. It is less clear, however, whether this positive correlation reflects a causal effect of schooling, or that individuals with a greater earnings capacity have chosen more years of schooling. If the latter possibility is true, the OLS estimates on the returns to schooling simply reflect differences in unobserved characteristics of working individuals, and an increase in a person's schooling owing to an exogenous shock will have no effect on this person's wage. (Verbeek, 2012, 4th ed., p.146)

With regards to our analysis of dairy farmers' reasoning behind their semen purchases and their willingness to pay for genomic technology, it is important to acknowledge these demographic characteristics: Although the collection and inclusion of these characteristics is beyond the scope of this study, we find it pertinent to discuss the findings of previous literature in the area. It is important to bear in mind how these individual farmer characteristics can bring about an influence on the selection of a particular semen sample, and are thus potential sources of heterogeneity in the semen selection process. Consequently, the findings in the literature should be considered when drawing conclusions from this present study results.

When discussing benefit transfers, the use of one *use value* in one study, called *study site*, for the assessment of a resource or service in another study, called *policy site* (sometimes findings of one country applied to another country), Freeman et al. (2014, 3rd ed.) bring up the differences that can arise when evaluating the value of one same resource at different places or across different population samples and attribute them either to *supply side* or *demand side* factors. The supply side factors can refer to the resource at hand while the demand factors relate to the demographic differences among the individuals "making use of, or at least valuing, the resource change" such as income, preferences and tastes (Freeman et al., 2014, 3rd ed., p.420). Similarly, when discussing variation in wages and different returns to schooling across people, Verbeek (2012, 4th ed.) alludes to observable characteristics in the people involved such as age or gender, and unobservable characteristics like innate ability or skill sets, for instance. In order to overcome the potential bias that these factors may impose on the analysis at hand, we follow Freeman et al.'s (2014, 3rd ed.) posture on using examples in the literature from contexts where the conditions and sample populations best approximate to our target population - Canadian dairy farmers - and contrast with other dairy farmers worldwide.

1.1 Supply Side Factors affecting the effectiveness of Breeding and Technology Adoption

While the traits being assessed and the use of genomic technology do not change in function, the perceived utility of these across a population does. As the theoretical overview of the hedonic price model has explained, the estimation obtained is a result of averaging out an aggregated set of individual, purchasing bids that vary in the willingness to pay for one same good or service. This section will elaborate on the ways in which the technology itself can present different challenges to its end users (in our case, using genomic technology in breeding and trait improvements for dairy producers) first and then touch upon some strategies used to induce a faster uptake. Finally, circumstantial factors influencing the needs of end users as well as the end results of the technology in that environment are discussed, as these can also affect the degree of implementation of a technology.

a) Nature of the technology

Diffusion of innovations scholars and literature on other technology adoption models emphasize the importance of technology characteristics and, more importantly, the perception of these by the targeted potential users, for its rate of adoption (Rogers, 2003, 5th ed.; Venkatesh, 2000; Chuttur, 2009; Howley et al., 2012; EduCenter, 2019). These are broadly classified as the relative advantage; its compatibility with existing values, experiences and needs of potential adopters; the degree of complexity involved in adopting and using the technology; its triability, or the ability to sample or test the alternative technology on a partial basis, and; its observable results in plain sight (Rogers, 2003, 5th ed.). The attributes that stand out hold the most influence for the uptake of a new technology are relative advantage and compatibility (Rogers, 2003, 5th ed.).

Empirically, this can be seen in Howley et al.'s (2012, p.174) analysis of AI adoption among Irish dairy farmers, where previous experience with the technology had a positive correlation with the probability of using AI, such that, "between 95 and 98 percent of farmers who used AI in any given year continue with its use in the following year." In contrast, Hailu et al. (2017, p.330) found that past genotyping experience among Ontario dairy farmers, although not statistically significant, did not ultimately "enhance the respondents' WTP for genotyping." Empirical information of farmers' uptake of genomics testing for breeding decisions further supports Hailu et al.'s (2017) findings. As of 2018, a mere 13 percent of the annual dairy heifer calves in Canada were genomically-tested (Harris, 2019). At a cost of $45 CDN for a "blanket test" in 2018, however, farmers still struggled to justify the investment on their heifers (Greig, 2018). The reasoning behind this was mostly associated with the expectations associated with its use, where producers quoted increasing animal sale prices as a main reason behind adoption, and the cost-benefit expectations, (i.e. its perceived relative advantage), may not have been met to warrant its use further (Greig, 2018). As Rogers (2003, 5th ed., p.15) explains, "it does not matter so much whether an innovation has a great deal of "objective" advantage. What does matter is whether an individual perceives the innovation as advantageous."

b) Market Structure: Supply of technology, cost levels and government interventions

Any costs associated with implementing a technology, including costs incurred to learn and adopt an innovation or to ship it to the farm, can also affect the uptake of a technology (Rogers, 2003, 5th ed.). More directly, the costs of the services like cost of semen and insemination had an effect on the probability of farmers adopting AI (Kaaya et al., 2005; Vishwanath, 2003). In Canada, Hailu et al's (2017) survey of Ontario dairy farmers studying their WTP for mastitis genotyping showed a significantly negative effect between the bid value (i.e. the suggested price for genotyping) and the probability of adopting the technology, where a $1 increase above the bid mean $77 would see a drop of 0.8% in genotyping adoption. Howley et al. (2012) corroborated this finding in their analysis of AI uptake among Irish farmers, where they found a negative association between veterinary services fees and AI adoption.

Alternatively, Miller and Tolley's study (1989) showed that market interventions, such as price supports, can speed up the adoption of new technologies. However, Rogers (2003, 5th ed.) cautions on the quality of adoption; incentives may trigger initial adoption, but the motivations for use may not be strong enough to guarantee long-term use of the technology. Therefore, when creating recommendations, caution must be taken on the extent of long-term effectiveness that can be drawn solely from implementing economic incentives to encourage adoption of a technology.

The extent of voluntariness in the adoption of genomics in breeding is an additional factor that is also relevant to this study, considering that the amount of power semen suppliers have on sire selection could influence the choices available for farmers to decide on a sample. This is a concept that is further considered in the Technology Acceptance Model (TAM) (Davis, 1989; see **Section 2.2**). In Canada, the supply of AI services is taken up by five companies; Semex Alliance, Select Sires, Alta Genetics, ABS Global and Genex-CRI (Beavers and Van Doormaal, 2019). Although semen prices are freely set by market forces and Canadian producers can buy samples internationally, the Canadian semen supply market is composed of just a few domestic AI suppliers. Early investment into the top 0.1 percent genomic animals allowed the AI companies and genetic corporations to take the lead over seed-stock producers and government herds (Hunt, 2014). Their larger financial resources afforded them more crossing combinations across their different females and top genomic-proven semen to funnel through the best specimens (Hunt, 2014). The degree to which this supplier structure could overtake the voluntariness of genomic adoption into breeding decisions by farmers is beyond the scope of this study, but should be considered when analyzing the results of our estimations.

c) Phenotypic expression of genetic potential: Nutrition, health, docility and environment

Although the pivotal decision for dairy producers lies in the selection of the bull, as it is the sire's genetic makeup that will infuse the cow herd with new attributes or ensure its current makeup continues, the expression of the genetic potential to its top performance also depends on other external factors. To some extent, the final productivity of a cow herd can be related to a four-legged milk stool; "The top of the stool represents herd performance. The legs represent nutrition, health, genetics and docility" (Rethorst, 2015, p.8).

Nutrition, other than affect pregnancy and the developing calves, can also affect the vigor of a bull's sperm, especially in the 60 days prior to collection or breeding, "since that is the turnover rate for new sperm" (Drovers, 2015)[40]. The semen itself may be jeopardized if, despite its outstanding genetic makeup and progeny record, the bull's nutrition is compromised in the last months prior to semen collection or breeding.

Environmental factors also influence the success of breeding and the productivity of the offspring; a study by Ohio State University in 2003, for instance, estimated that heat stress was responsible for \$2.36 billion in losses per year to the US livestock industry (Buck, 2018), while the University of Florida's research on Brangus cows found that after 39°C, cows would eat less and ultimately produce less meat and milk (Buck, 2018). Additionally, heat stress can directly impact fertility by damaging semen quality and thus, result in less pregnancies (Henderson, 2015). Further, under-nutrition and over-nutrition of pregnant dams reduces the number of muscle and fat cells of the developing calf (Rethorst, 2015) and thus impairs the full expression of that calf's genetic potential. Among the many factors affecting calving, aside from geographic region, environmental temperature and dam nutrition and condition, farmers and industry experts also highlight factors like length of breeding season, temperament, age of the dam and its pelvic area, along with calf size at birth as significant factors influencing the farmers' investment and success in cow herd management (Barham, 2015). Similarly, health traits and resistance to key diseases as well as mobility and body condition scoring have become important to producers (Boettcher and Van Doormaal, 1999).

1.2 Demand Side Factors: Farmers' sociodemographic and operation-specific observable factors

Demographic elements intrinsic to the decision-makers can also play a role in shaping perceptions towards a good or service (Freeman et al., 2014, 3rd ed.; Rogers, 2003, 5th ed.; Howley et al., 2012). This section will touch upon select stated preference studies in the literature that evaluated the effect of these intrinsic characteristics of farmers on their adoption of new technology. The nature of our data only allowed for price data and characteristics related to the semen doses sold and bought in the market to be used, not to those associated to farmers or their operations. Therefore, for the purposes of this study, we restrict our analysis to revealed preference data, and work under the assumption that

[40] Cows with a BCS of 4 will drop to 60 percent likelihood to be in heat in calving season (Drovers, 2015).

these farmer and operation-specific factors have not changed the distribution of the Canadian dairy landscape during the time period considered, but that the differences continue to balance out over the population sample for which the semen transactions were captured. Considerations where this assumption is loosened are discussed in the last chapter, but will not make part of the analysis of this study.

a) Experience, Age, Level of education, familiarity with technology

Previous studies have found years of education and technology adoption are positively- associated, such as (Prokopy et al., 2008; Kaaya et al., 2005; Howley et al., 2012). Their considerations are supported by El-Osta and Morehart's dairy study (2002), which reported that farmers' age as well as the size and degree of specialization of their operation influenced the adoption of capital-intensive technology, while only farmers' level of education and the size of the operation affected the uptake of management-intensive technology. Similarly, research in the US dairy sector by Khanal and Gillespie (2011) showed that younger farmers and higher education levels had a positive relation with the adoption of breeding technologies like AI, sexed semen and embryo transplants. Contrastingly, however, Hailu et al. (2017) found their survey of Ontario dairy producers were along the national age average of 50 years old and older, and their perception towards genomics was mostly neutral to positive. The marginal effects from these demographic and farm characteristics did not have a statistically significant effect on the mean WTP for genotyping or on the probability for genotyping estimated for the Ontario dairy farmers sample (Hailu et al., 2017).

b) Farm structure

Farm characteristics such as the size and the type of operation as well as labour supply can also play a role in adopting new technology (Howley et al., 2012). A study on the use of AI among Irish dairy farmers, for instance, revealed that farmers with an off-farm job were "much less likely to adopt AI," while farmers with children were more likely to adopt it (Howley et al., 2012, p.174). Howley et al. (2012) attributed their findings to the time constraints farmers may face with an additional job in the former and the forward-thinking plans for farm succession working as an incentive for the latter. Observations from the Australian dairy system by Martin-Collado et al. (2015), however, suggest that the type of operation or breed cannot be used to forecast farmer attitudes on genetic innovations in breeding: The authors noted that the potential effect on the selection of a specific, single trait was nullified when the attitude towards the entire *package* of traits was analyzed.

c) Farm size, gross margins

Howley et al. (2012, p.175) found that Irish farmers with "higher gross margins per livestock unit were likely to use AI than farmers with relatively lower gross margins." Previous studies in the literature have also found an association between early technology adoption and large farms (Jamison and Lau, 1982; Feder et al., 1985; Klotz et al., 1995). Further, the observations point to a potential case of endogeneity where farm size dictates technology adoption (Reimund et al., 1981; Gillespie et al., 1997). On the other hand, Rogers (2003, 5th ed., p.289) recognized that "economic factors do not offer a complete explanation of innovative behavior," and in fact, certain studies on agriculture, for instance, also show that not all wealthy farmers translate into immediate adopters of technologies. Survey results for Ontario farmers examined by Hailu et al. (2017), also suggested that the demographic and farm specific characteristics had no statistically significant effect on their estimation of WTP for mastitis genotyping. Lastly, Howley et al. (2012, p.175) found farm size and AI adoption were negatively associated, and accredited it to the coefficient having captured "a more extensive rather than intensive farmer enterprise."

1.3 Demand side factors: Unobservable characteristics differentiating farmers

The changing landscape in farm numbers also had an impact on the management approach of operations, where farmers increasingly took a bigger role of a "supervisor and financial manager" (Boettcher, 2005, p.8). Consequently, the focus on optimizing efficiency could have shifted the prioritization of sire traits as costs of production were brought to the forefront of producers' minds (Boettcher, 2005). Similarly, the producers' risk preference will also come into play when considering changing strategies in their operation, or adopting genomic technologies in their breeding decisions. This section will conclude the discussion on inherent characteristics of farmers (and their operations) that can also play a role in the decision making process of selecting a bull and which have been studied in the literature before. While our study on farmers' valuation of sire traits will restrict its analysis to revealed data analysis, we find these endogenous sources of shift a valuable layer for future model estimations and worth considering when interpreting our results in the following chapters.

a) The management component

Good management is important for the sustainability of a farmer's operation and the optimal performance of their crops or cattle. Ultimately, a key factor in an operation's success is the innate managerial skills of producers. As much as a herd's genetic makeup and their nutritional diet impact a farm's productivity level by 33 percent each, a third of the operation's success relies on a farmer's managerial skills (Hunt, 2019b). Moreover, the other two thirds of the operation's profitability are determined by the farm manager, such that the inherent management skills of the farmer constrain or enhance the farm's potential directly. Similarly, Hailu et al. (2017, p. 332) identify the gaining productivity hikes from using genomics testing depend on producers' integration of this technology into their current management plans, as "genomic selection for disease resistance will not be a perfect substitute for inefficient herd management practices that may cause animals with lower susceptibility to get sick."

b) Risk preferences

Uncertainty and the associated risk involved in farmers' investments is an intrinsic aspect of agriculture, as decisions need to be made well ahead of time before the growing season or the sale price and market conditions are settled. Heady and Jensen (1954) breaks it down into six different types: (1) Market price, (2) production numbers due to weather or disease, (3) performance of new techniques or production methods, (4) legislation, (5) contracts with other parties like banks, processors and (6) personal health risks. As a result, we assume that producers operate in a range that considers the worst-case scenario and the best-case scenario. Ultimately, it is clear that the "risk preferences of farmers are also important in influencing the technology adoption decision, especially if capital-intensive technology costs are irreversible (Howley et al., 2012, p.172; Sundig and Zilberman, 2001)."

More concretely, in the case of cattle operations, "if [farmers] use only one bull but make a bad decision, the entire calf crop will underperform" (Pipkin, 2015, p.20). The hedonic price model can also reveal the average level of risk aversion among farmers in the Holstein semen market: As

Richards and Jeffrey (1996) explain, risk preference is also measured implicitly through their choice of bull. While the number of daughters was used as a marker for popularity and a proxy for repeatability, it indicated to producers the uptake level of this sire into herds and vouch for the cows' longevity.

Similarly, the hedonic price model will also measure the average producers' tendency towards adopting genomic technology in breeding decisions.

Farmers' likelihood to adopt a technology will be greatly influenced by their attitude towards risk (Rogers, 2003, 5th ed.; Gillespie et al. 2004; Baerenklau, 2005; Hailu et al., 2017). Studies in this area have failed to arrive at a consensus, however, on the overall effect risk attitudes have on technology adoption, and rather yield examples for opposing trends. Generally, theory supports risk-averse consumers have "greater incentives to adopt risk-reducing technologies" (Hailu et al., 2017, p.319). Unexpectedly, the survey results in Hailu et al. (2017) study of Ontario dairy farmers showed that those with a higher risk tolerance had a higher WTP for mastitis genotyping. Additionally, their findings revealed that risk tolerance had no significant effect on the WTP of producers with a higher degree of mastitis concern and that, once the interaction term between risk tolerance and social networking was added to the WTP estimation or genotyping for mastitis resistance, the effect of the risk coefficient on WTP was rendered insignificant, while the joint effect was positive and significant. The result points to the possible misspecification error that can be incurred when the interaction effect is omitted from the analysis.

c) Degree/Extent of Social networking: Peers, Participation in extension services and availability

The exchange of information, in passive or active forms, between farmers and their neighbours or educational extension services or industry experts become economically relevant when their effect has an impact on producer's response towards a new technology and adopting it in their operation (Sauer and Zilberman, 2010; Rehman et al., 2007). Previous studies by Prokopy et al. (2008) and Boaitey (2017), for instance, found a positive relation between adoption of better [management practices] and environmental awareness, the use of social networks and the access to information. Similarly, Hailu et al.'s (2017) study on willingness to pay for mastitis resistance genotyping found a strong interaction effect between this measure and farmers' risk tolerance, as well as their level of social networking, when assessed jointly as well as separately[41]. Further, the survey found most farmers had a neutral or positive attitude towards genomics, and “only 12.58% of respondents reported that they feel negative about genomics” (Hailu et al., 2017, p.326).

2. Technology Adoption models

The improvement of genomic technology and the enhancement of attribute measurement methods helped to make these tools more accessible to producers and bring them to the forefront of sire selection techniques. As Miglior et al. (2017, p.10265) note, “a pivotal development in regard to trait selection is the advent of genomics, which has [...] provided a new opportunity to select for traits that were prohibitively expensive to measure in the past.” Although the hedonic price model did not set out to measure technology adoption specifically, its valuation of the embedded sire traits in semen transactions can indirectly expose the willingness of farmers to use genomics for the improvement of low-heritable traits. While the scope of this study does not extend into the detection of adoption phases of the dairy producer population in Canada, we find it pertinent to delineate the main technology adoption models to further account for our results in the following chapters.

2.1 Rogers’ Diffusion of Innovation Model

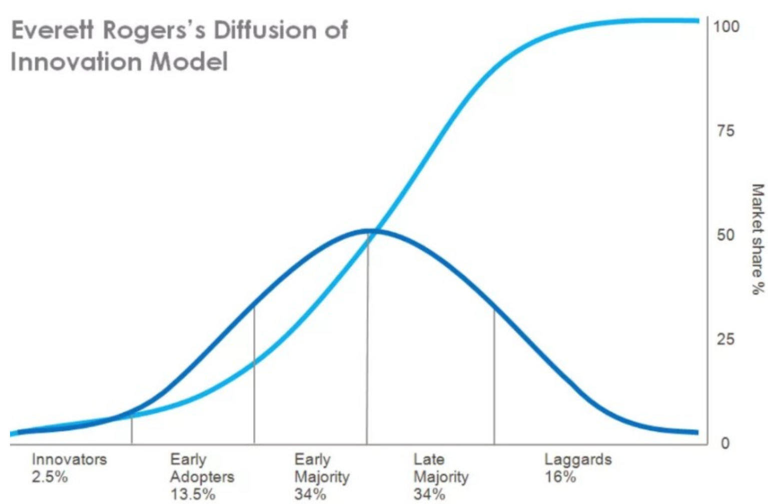
Roger’s Diffusion of Innovation Model delineated the rate of adoption of new technologies. The model characterized consumers into five adoption categories, each holding a certain proportion of the market (see **Figure 2.1**). While innovators are the earliest, most aggressive technology adopters, they only comprise about three percent of all consumers in the market. Innovators usually are comfortable with venturing into new territories despite the high level of uncertainty and will be able to cope with, or absorb high risk, and thus, work as importers or *gatekeepers* of novel ideas (Rogers, 2003, 5th Ed.). *Early Adopters*, on the other hand, do not seek to invest unless they sense a fit in their operation. Their adoption sparks the beginning of broader, popular uptake (Rogers, 2003, 5th Ed.). In contrast, the *Early Majority*, comprising a third of the market, will wait for hard, strong points of reference before embracing new technologies and the *Late Majority*, also composed of a third of the consumers, will further await for

[41] WTP values were higher for producers that had a greater number of social interactions; one more peer in their network would bring forth an increase in \$3.10 on the WTP for mastitis genotyping and a 2.6% rise in the probability to genotype their herd for mastitis (Hailu et al., 2017).

companies to specialize before investing in new technologies. Adoption can become the result of society pressures that finally overtakes their skepticism to invest their limited resources into the new idea (Rogers, 2003, 5th Ed.). Finally, *Laggards* will hold on to the old ways and postpone the adoption of new procedures or technologies as long as possible (Matthews, 2012)[42].

Rogers confirmed that this S-shaped pattern on the diffusion of a successful technology adoption in a group or organization was “a *general process*, not bound by the type of innovation studied, who the adopters were, or by place or culture” (Rogers, 2003, 5th ed., p. xvi; see also Mort (1953) comparing the spread of kindergarten and driver training education; Menzel and Katz’ (1955) study of the uptake of an antibiotic (tetracycline) by doctors; Ryan and Gross’ (1943) findings on the diffusion of hybrid seed corn); Deutschmann and Fals Borda (1962) in a Colombian town (on the adoption of six different innovations over time[43]). In our research, we can come across this dynamic indirectly through an observed change in values for bull traits that are related to enhanced genomic selection methods, and thus reflect an increasing trend of trust towards the technology and the adoption of genomics in sire selection between 2008 and 2016.

Figure 2.1 Diffusion of Innovation Model



SOURCE: Matthews, 2012

[42] Matthews, 2012.
[43] Namely, chemical fertilizers, potato fungicide, spray guns for insecticides and fungicides, concentrated feed for poultry and cattle, cholera vaccination for poultry and the use of a new potato variety (Deutschmann and Fals Borda, 1962).

2.2 TAM Model

The Technology Acceptance Model (TAM) directly addresses the way Information Systems users accept and take in a particular technological innovation (Davis, 1989). The model explains the uptake of a technology by an end user depends on its Perceived Usefulness (PU) and its Perceived ease-of-use (PEOU) (Davis, 1989). Ultimately, the key takeaway from this model's insight on technology use for our present analysis of semen purchases is that adopting a technology is influenced by elements beyond the nature of the technology itself, or the individual's objective needs for the technology. In addition, certain factors affecting technology adoption and decision-making highlighted previously resurface in this model again such as the degree of social influence, experience and perceived output quality. As Martin-Collado et al.'s (2015, p.4148) analysis clearly showed them, "[w]e have seen that differences in patterns of trait preferences in the Australian dairy industry are intrinsic in farmers and not to the production system or the breed."

2.3 Case Study: Australian Dairy Farmers

A more recent study on Australian dairy farmers' preference for innovations on cow attributes found farmers did not display extremely positive or negative attitudes toward genetic innovations, even when separating them into different categories (Martin-Collado et al., 2015). Their analysis divided their farmer sample (n=551) into three groups or farmer typologies:

i) Production-focused farmers (n=192); they favored improving traits for protein yield, feed efficiency and longevity. The traits they most focused on when making decisions were protein yield, cow live weight, milking speed, lactation persistency, feed efficiency and longevity. Their least important traits were related to mastitis, lameness and mammary system. They were the oldest cohort among the three typologies.

ii) Functionality-focused farmers (n=172); these producers were most interested in fertility, then calving difficulty, lameness, and mastitis. They mostly made breeding choices based on these traits and also temperament.

iii) Type-focused farmers (n=187); this group preferred improving mastitis, longevity and mammary system traits but also cared most for traits like type, fertility and temperament, in addition to the firstly-mentioned traits, when making decisions. In contrast with the other groups, they found protein yield the least important trait. They also found genetic prediction tools like EBV and APR index[44] values less influential to their decision than the other groups, and had less confidence in the accuracy of the relative weighing of the traits and the traits chosen as representative to their operation needs (Martin-Collado et al., 2015).

[44] The Australian Profit-Ranking (APR) index: a weighted average of 9 bull traits used to 'grade' Australian dairy sires. The traits consist of production attributes; milk, fat and protein yield as well as cow live weight, and non-production attributes; longevity, fertility, resistance to mastitis, temperament and milking speed (Martin-Collado et al., 2015).

While the groups differed on age, attitudes towards genetic selection and the decisive traits for bull selection, they did not depend on herd size, calving or feeding system nor breeds used (Martin-Collado et al., 2015). Interestingly, however, a separate cluster analysis solely on the traits found that most Holstein farmers fell into the type-focused group and Jersey farmers usually were classified in the production-focused group (Martin-Collado et al., 2015). In addition, the authors also observed that the categories were not discrete, as several farmers had intermediate preferences between those groups (Martin-Collado et al., 2015).

Farmer and operation specific characteristics in this study had effects on single traits assessed independently, but once aggregated, "these effects vanished when analyzing all preferences as a whole" (Martin-Collado et al., 2015, p.4157). Further, the average results did not match up with any of the farmer typologies found in the study, which led to the crucial observation that mean values cannot be interpreted as a representative population pattern when it involves issues with high heterogeneity levels, like farmers' trait preferences for bull selection (Martin-Collado et al., 2015). This finding was also corroborated by other studies in developing countries (Ouma et al., 2007; Nielsen and Amer, 2007 and Sy et al., 1997). As authors noted, not only can the averages give "an incomplete and biased view of the farmers' preferences," but it can also blur the distinction among the different types of farmers with different breeding needs. Ultimately, this error can further hinder the development of segment-tailored indexes that will increase genomic innovation adoption according to the different needs of each farmer typology (Martin-Collado et al., 2015, p.4157).

IMPLICATIONS FOR THE CANADIAN CONTEXT

In concrete terms, these results would lead our Holstein-focused study to expect the semen transactions to show farmers favor similar attributes as this third group of Australian dairy producers. Moreover, it would further suggest weighted averages such as the LPI in the Canadian context would take the back seat in the decision-making process of breeding choices. The present study seeks to fill the gap in the literature in regards to the breeding decisions of Canadian dairy producers through time. While studies like Martin-Collado et al. (2015) point to a greater focus on type characteristics, the dairy organizations in Canada hold that farmers' preferences may be changing towards production attributes. Establishing an econometric model that can tease out the prioritization process that Canadian producers follow when selecting a semen option promises to shine light on producer behaviour and willingness to adopt genetic innovation in certain traits. More specifically, the findings can help regulating institutions, producers and Artificial Insemination units select the right sire for their future herd stock.

E. THESIS OBJECTIVES: RELEVANCE OF STUDY IN LIGHT OF BODY OF LITERATURE AND CANADIAN DAIRY MARKET

The main purpose of this study is to analyze the valuation of bull attributes by Canadian dairy farmers during their breeding decision process: Using a Hedonic Price Model, we seek to establish the relative ranking of these attributes based on what is revealed from real-market semen transactions and identify any potential variation in preferences over time. Secondly, through the use of historical data from bull proofs published by Holstein Canada, the Hedonic Model results and the descriptive statistics from these proofs will be compared against the latest industry observations by Richards and Jeffrey's (1996) and the 2016 LPI weightings to confirm if farmers' valuation has remained production-trait focused, and that the weights accurately reflect the ranking revealed through market transactions. Correctly identifying the attributes that move producers to make a breeding decision helps us to better understand the place that genomic data innovation would have in the process.

Measuring the extent of the benefit this type of genomic innovation would have on producers, in terms of production attributes (e.g. average daily gain or daily milk production indices), and how they translate to increased profits or reduced costs, will allow us to properly estimate the value that these technological innovations would be worth for producers. Furthermore, it can aid the government and private dairy sector to set appropriate plans in motion - including policies, extension services, support mechanisms and breeding priorities - to encourage producers to consider genomic testing in their breeding selection process.

Chapter 3 . DATA DESCRIPTION AND ECONOMETRIC METHODOLOGY

This thesis seeks to reveal the ranking of the different sire attributes in dairy farmers bull semen selection across Canada. Further, this analysis looks to carry on from the last analysis done on farmer valuation of sire attributes by Richards and Jeffrey (1996), and evaluate the claim that a shift in preferences from type to production attributes has occurred, as well as evaluate the possible influence of genomics in selection decisions. In order to carry on this assessment, a hedonic model of bull semen prices was chosen to identify the implied monetary values of relevant sire attributes in breeding decisions based semen dose transactions. The key sire attributes used to explain the market value of Holstein semen from different bulls in this analysis were selected based on their economic values (Shook, 1989) as well as examples in the literature, as explained in the previous chapter. The physical database used to study farmer's attribute valuation pulled values from the information in the annual proofs of each registered bull in Canada and semen purchases in the Canadian Holstein market. The nature of the database used in this study, the econometric modeling employed for the estimations -from the *general* formulae representing the hedonic price model, to the variables included, and the different functional forms used and testing conducted-, are explained in this chapter. Summary statistics for the main database as well as for supporting historical data used for background and context are also presented here. For quick reference, a summary table for the main variables used in this study can be found in **Appendix 3**.

A. DATA AND SUMMARY STATISTICS

The panel data used in this study was provided by the Miglior (2017) and it consisted of 8 711 entries for several sires across different insemination dates, with purchases spanning through the period of 2008 to 2016 (Miglior, 2017). This data compilation contains the values for the key bull characteristics as well as sale prices for specific bull semen associated with each sire, in different periods.

Overall, this series had 4 581 different bull specimens, although the number of bulls and the identity of specific bulls did not remain the same over this time period[45]. Further details on the nature of the database and the implications for the econometric modelling are explained in this section.

In addition, this study also compiled a database from selected annual bull proof publications of Holstein Canada for the years of 1995, 2000, 2005 and 2008. The average score values will contribute in identifying the traits of different bulls that were popular before genomics was heavily used in Canada, starting 2008. A description of the data and the main trends observed in trait score values is covered briefly in this section, as a more thorough examination will be presented in the next chapter.

1. Historical data from the Holstein Canada Association: Bull proofs from 1995, 2000, 2005, 2008

In addition to the main dataset that will be used for the hedonic model analysis, historical bull data (attribute scores) from Canada Holstein Association publications will be used. Although the data does not provide semen prices, the records contain similar constructs to the 2008-2016 data in terms of the attribute scores. Even without the price data, however, examining the fluctuations in trait average values from this bull information could prove of interest to the industry to further aid in identifying the popular traits in Canadian bulls. The approach to pick any shifts in semen demand or supply of characteristics will be evaluated in a couple of ways; by looking at the range of values in the population of the available data (1) and; by looking at the range of values for the top 100 LPI-ranking bulls from the general population (2), as well as by comparing these two groups against each other for every year of available data (3) (a within-year comparison). Since digitalizing the entire Holstein database was a mammoth task, descriptive data from four issues was captured to achieve these purposes,

[45] Panel data refers to a cross-section of individuals (or units) observed over time, with different profiles possible for the data, such as: (1*) long and narrow;* long period of time but narrow number of individuals, (2*) short and wide;* short amount of time but many individuals, (3*) long and wide;* both dimensions are large. Our data file was long and narrow, often referred to as an unbalanced panel, where "individuals are not always interviewed the same number of times" (Hill et al., 2011, 4th ed., p.539). In other occasions, this is simply defined as pooled data. However, as Hill et al. (2011, 4 ed., 239) note that, "it is not possible to have data that combines cross-sectional and time-series data which do not constitute a panel," we address this data as an unbalanced panel that is long and narrow throughout our analysis.

starting with 1995, followed by 2000, then 2005 and ending with the last available publication on print, 2008.

The objective is to assess the broad trends in type and production attribute scores by bull starting from the last-available assessment on Canadian producer behaviour for dairy bull semen selection, the study by Richards and Jeffrey (1996), up to the point where this study's comprehensive database started, 2008.

The following table of descriptive summary statistics shows that production traits (i.e. milk, protein and fat scores) perceived the smallest gains over time when compared to the other key attributes. More specifically, in terms of net yield in kilograms, milk rose by 5.41 percent from 2000 to 2005 and by 1.54 percent between 2005 and 2008, while fat increased by 3.63 percent and 2.55 during the same time periods, but protein only increased by 1.5 percent. When we observe the EBV scores, however, these milk components actually observed reductions in their average values over time[46]. Further discussions on these observations can be found in the following chapter.

In contrast to the production trait pattern, feet and legs observed a constant rise of 14 percent gains between 2000 and 2005 as well as 2005 to 2008, while conformation grew 9 percent in the first period and nearly 14 percent in the second period. Lastly, the most notable gains were observed in dairy character for 2005 against 2000 values (24.48%) and mammary system for 2005 to 2008 (22.8%).

[46] One issue encountered when attempting to compare the changes in these values arose from the changes in scoring methods. In 1995, the milk, fat and protein proofs were calculated using breed class average values and recording the deviation beyond or under this breed average (BCA) (Richards and Jeffrey, 1996).

Table 3.1 Descriptive statistics for key bull attributes in annual bull proof publications for years 1995, 2000, 2005 and 2008 (Holstein Canada, 1995; 2000; 2005; 2008)

	1995	2000	2005	2008
MILK	5.547	1185.867	983.829	859.522
FAT	5.71	40.607	33.864	27.739
PROTEIN	5.892	38.675	32.803	27.994
2yr avg Milk kg	7247.544	-	-	-
ME Milk kg	-	10519.97	11089.17	10918.26
2yr avg Fat kg	269.103	-	-	-
ME Fat kg	-	383.756	397.683	407.842
2yr avg Prot kg	230.535	-	-	-
ME Protein kg	-	334.905	339.34	344.663
Final Class/CF	2.867	-	-	-
CONF	-	5.379	5.87	6.6821
LPI	460.254	1023.673	951.207	977.219
ETA Capacity	1.984	-	-	-
Frame/capacity	-	3.061	3.185	-
ETA Feet Legs	1.497	3.231	3.685	4.227
ETA Mamm. S	2.749	4.846	4.913	6.042
No daus class'd	255.881	-	-	-
SCS	-	2.9703	3.004	2.992
HL	-	3.088	3.037	102.352
Dairy char.	3.563	4.477	5.594	-
Temperament	-	-	-	97.916
DF fertility	-	-	-	98.368
ET births	1134/1610	576/759	348/426	392/475
ET %	70.43	75.89	81.69	82.53
Total bulls	1610	759	426	475

On the other hand, during the data capture of these publications, the inclusion of new attributes or changes in existing ones, such as the introduction of somatic cell scores, conformation and herd life in 2005, as well as scoring dairy character as temperament instead, in 2008 is evident. Simultaneously, the omission of other categories like the semen availability, final class and number of daughters classified reported in 1995, and the removal of capacity scores in 2008 make comparisons across the years difficult.

Another marked trend between the 1995 data and the other years was the precipitous decrease in sire choices available for farmers across Canada. The total number of bulls fell from 1675 in 1995 to less than half by 2000 (n=759), and to 475 by 2008. Further, analysis of the recorded bulls showed very little overlap of registered bulls between all the year intervals: From a total of 1593 bulls in 1995 and 759 in 2000, only 57[47] showed on both years, while 40[48] appeared in both 2000 and 2005, and 99 were registered in both 2005 and 2008.[49] Lastly, only one bull, Comestar Lee (CANM5319769), showed up throughout all the bull proof publications. A more thorough *panel-like* comparison of the trait scores was thus unfeasible under such small observation sizes. As a result, our analysis of this data in the next chapter will limit itself to analyzing the fluctuation of the entire bull registry's average values over time and an additional comparison between the entire sire pool and a sub-category of the top 100 sires as denoted by their LPI scores.

2. Semen data on Canadian market transactions: Panel data from 2008 to 2016

The data provided by Miglior (2017), was sourced from SEMEX records of semen transactions which occurred over the 2008 to 2016 period. In contrast to Richards and Jeffrey's (1996) cross-section database, this study's underlying data to study farmers' valuation of different sire attributes is a panel series. However, individual regressions for each time-period will also be considered in this study, in order to analyze if a distinct break in attribute preferences, or variability in the significance of the attributes to the semen's price, can be evidenced from the year to year observations.

The observations in the database from Miglior (2017) consist of an entry per transaction with the selling semen price (cost in CDN), the identification code of the bull that it is sourced from, the minimum and maximum insemination dates, the total number of active days for that bull, the total inseminations performed for that particular purchase event, the associated scores for *production* attributes such as EBV Milk; EBV Fat and; EBV Protein[50]. In addition, indexes for *type* attributes like Conformation; Feet & Legs; Mammary system; Somatic Cell Score (SCS); Herd life (HL) and; Daughter Fertility (DF) , as well as the average LPI score for each bull (over the active period) are presented. A summary of the variables and their definitions can be found in **Appendix 3**. The data per bull is used as the basis of the hedonic bull semen model.

[47] An additional 4 bulls were found for 1995, 2000, and 2005.
[48] Other than the 4 bulls overlapping for 1995, 2000 and 2005, 19 bulls were registered for 2000, 2005 and 2008.
[49] As noted previously, there were 19 additional bulls registered for 2000, 2005 and 2008.
[50] Estimated Breeding Values (EBVs) are "a value which expresses the difference (+ or -) between an individual animal and the herd or breed benchmark to which the animal is being compared. EBVs are reported in terms of actual product e.g. days, kg of weight or mm of fat depth, etc." (The Cattle Site, 2011).

In an effort to analyze the semen transactions from year to year, the overall panel database was divided into separate, cross-sectional series to compare the potential change in attribute valuation over time, as well as to maintain a parallel approach to Richards and Jeffrey's (1996) and Walburger and Foster's (1994). Nevertheless, multiple years were associated with a single semen entry in this database, given the nature of the time range used -the minimum and maximum insemination dates often stretched over multiple years-. Therefore, when the date ranges showed that a semen transaction had active inseminations over more than one year period, these entries appeared under all the separate cross-sectional series created for each year with active insemination bulls. As a result of these multiple transactions per year and semen's active use spanning over multiple time periods (as the dates for min. and max. insemination time crossed over years).

The entries were organized by LPI scores in descending order, and grouped by bull code. The sorting of the data revealed an unbalanced series, where some bulls had up to 18 transaction entries, and others had merely one entry over the entire time range. Moreover, some year periods have multiple transaction entries per bull while other year periods fail to have this bull at all; only 13 bulls from the total 4579 of registered sires are present throughout the entire data period. This situation, together with the large cross-sectional dimension of the data, limited the time aspect of this study's working database, so estimations will be carried on without performing pre-emptive tests for stationarity. The entirety of the panel data, set over the period 2008 to 2016, is thus modelled under the standard Tobit I model and an additional, Cragg Double-Hurdle specification resolving for the censored price variable. The unbalanced nature of the panel series is not the focus of this case study, however, and for the purposes of this study, the econometric estimations are carried on under the assumption that the missing observations in the series were sourced exogenously. Alternative approaches for relaxing this assumption and testing for the potential sample bias are touched upon in the final concluding chapter of this thesis.

Furthermore, as was the case for the last studies on Canadian farmer behaviour during semen transactions in the dairy and swine industries (Richards and Jeffrey, 1996; Walburger and Foster (1994), and following the previous methodology for recording of the sales data, any semen price under

$5 CDN was coded as zero in Miglior's (2017) database. Similarly to Richards and Jeffrey's (1996)[51] and Walburger and Foster's (1994)[52] studies, the panel data provided by Miglior (2017) presents a bunching of values at zero dollars for 48.91 percent of the total 8712 semen transaction observations (4261 of the prices were registered as zero). These zero observations suggest the lack of interest in that particular bull's semen by farmers or a lack of interest in selling the particular semen by sales agents or both. Summary statistics for the overall database as well as for each year period is shown below.

The large number of censored observations occurring at $5 CDN introduces a source of bias into the database. This is a case of Type I censoring, where a sample entry is observed incompletely: While the regressors (x) are always observed, only a subset of the possible values of the dependent value (y* as opposed to y), can be observed (Cameron & Trivedi, 2005, p.532). The remaining possible values are unknown as they become set to a threshold level L as follows;

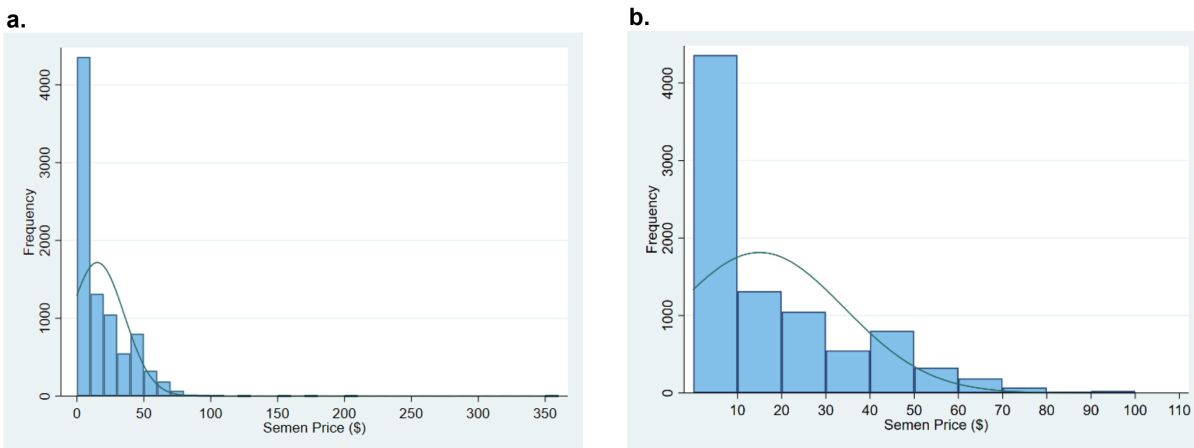
$$y = \begin{cases} y^*, & if\ y^* < L \\ L, & if\ y^* \leq L \end{cases}$$

In our case, the threshold value is $5 CDN and, whenever the semen samples are sold under this threshold, the transaction was recorded as sold for $0 CDN, but the data on the sire attributes (in this case, our regressors) are completely observable. Under this censoring-from-below circumstance, the expected error term will be positive, and the conditional means, in turn, will be "nonlinear so that OLS estimates will be inconsistent" (Cameron & Trivedi, 2005, p.531). Tracing the demand curve for these semen transactions solely using an OLS model would produce a slope coefficient biased downward. Consequently, an OLS regression would project a flattened fitted line (Cameron & Trivedi, 2005, p.531). Truncation of the database, that is, to completely remove the 4 261 observations with $0 as a cost "entails greater information loss than does censoring" (Cameron & Trivedi, 2005, p.529), so a maximum-likelihood estimation, namely a Tobit model, is the first baseline approach to assess this data without incurring into greater data loss. Although this will imply "strong distributional assumptions", such as a latent variable that follows a normal distribution with a constant variance across observations ($y^* \sim$

[51] N= 692 purebred Holstein bulls; 80.5 percent of the observations had zero as a semen price (Richards and Jeffrey, 1996)
[52] N= 1 175 boars in total; 41 percent of the boars sale prices are not recorded (Walburger and Foster, 1994)

$N[x'\beta, \sigma^2]$), simply running a linear regression using OLS would lead to inconsistent estimators and not representative marginal effects (Cameron & Trivedi, 2005, p.530).

Figure 3.1 Semen Price distribution for panel observations, 2008-16,
(a) All observations (b) Observations under $110



The semen price values ranged from $0 to a maximum of $355 per dose across the 8 711 observations. While the mean price was $15.19, the median was $8, with 75 percent of the observations falling under $25 value. Data sourced from Miglior (2017).

Furthermore, as we analyze the histogram for semen prices over the years of 2008 to 2016, we can observe more clearly the high number of transactions accumulated at $0 and the long tail distribution of prices spreading up to $355. In cases where such a large proportion of the dependent variable is unobserved, like in this dataset, where the times that transactions were down-priced at $0 are indiscernible from times when no transaction took place, there is a high risk of falling into omitted variable bias (Greene, 2012, 5th ed.). This implies that the amount of times that producers chose to participate in the Holstein semen market is underestimated, and the bull-trait preference structure of these producers may not be captured in the estimation of the hedonic price model. Further, the histogram of the semen prices helps us understand better how the dataset fails to fully represent a censored normal distribution, as expected under a Tobit model. This study will thus consider a novel approach to modeling the data; the alternative use of a Cragg Double-Hurdle. This model separates the estimation process into a selection stage (i.e. the first hurdle, where participation in the event, such as purchasing a semen sample, takes place) and the *decision-spending* stage, where the level of expenditure is studied (in this case, the hedonic model where semen price is a function of the bull traits) (Duan et al.,1983). As a result, this model relaxes some of the restrictions that the single estimation of the Tobit model imposes on the estimators of the dependent variable (e.g. the effect of the bull attributes on semen price): “The Tobit model assumes that the dependent variable follows a censored normal distribution where the censoring function and the uncensored expenditure function have the same coefficients” (Duan et al., 1983). The empirical methods are explained in further detail in this chapter in Section B.

Table 3.2 Descriptive statistics by year and period (2008-2016, Jan-July, Aug-Dec), and for aggregate observations (entire panel series)

	2008		2009		2010		2011		2012		2013		2014		2015		2016		PANEL
	Jan-July	Aug-Dec	Jan-July	Aug-Dec	Jan-July	Aug-Dec	Jan-July	Aug-Dec	Jan-July	Aug-Dec	Jan-July	Aug-Dec	Jan-July	Aug-Dec	Jan-July	Aug-Dec	Jan-July	Aug-Dec	2008-2016
Bulls no.	529	601	786	819	1080	1078	1202	1225	1335	1327	1500	1515	1561	1586	1570	1995	1496	1175	4579
Total Observ. (N)	830	966	15456	1445	1715	1706	1816	1791	1935	1935	2166	2202	2343	2273	2322	2279	2266	1747	8711
Semen Price	6.46	7.92	9.76	9.42	9.52	10.24	9.84	10.73	10.88	11.23	11.84	12.09	12.12	12.73	12.60	13.57	14.37	15.51	15.20
EBV Milk	1002.12	1062.13	1117.27	1084.91	1064.49	1115.40	1115.86	1139.51	1188.95	1240.23	1272.47	1280.54	1272.42	1296.25	1303.32	1313.54	1302.77	1363.81	1215.47
EBV Fat	35.35	37.20	42.57	42.54	42.62	46.73	49.23	50.98	53.31	55.29	58.01	59.17	59.34	61.03	61.81	62.95	63.93	66.81	54.63
EBV Protein	33.10	34.58	37.23	36.69	36.07	38.27	39.39	41.17	43.50	45.12	47.14	48.12	48.42	49.60	50.57	51.37	51.61	53.65	45.27
Conformation	4.73	6.07	7.65	8.40	8.60	9.46	9.74	10.15	10.21	10.47	10.56	10.83	11.05	11.45	11.36	11.52	11.47	11.69	9.72
Mamm. Syst.	4.15	5.41	6.86	7.46	7.54	8.45	8.67	8.93	9.09	9.34	9.46	9.72	9.94	10.31	10.25	10.48	10.45	10.70	8.80
Feet Legs	2.46	3.66	5.09	5.56	5.90	6.34	6.38	6.72	7.00	7.38	7.66	7.89	8.02	8.30	8.30	8.52	8.63	8.89	7.12
Daughter Fert.	98.96	99.13	99.30	99.58	99.78	104.28	99.95	100.10	100.31	100.19	100.34	100.65	101.19	101.50	101.78	102.27	102.52	102.82	101.01
SCS	2.97	2.97	2.95	2.93	2.91	2.88	2.87	2.86	2.85	2.84	2.84	2.83	2.82	2.80	2.80	2.79	2.79	2.78	2.85
HL	101.20	101.84	102.69	102.90	103.58	104.28	104.86	105.27	105.78	106.13	106.56	106.99	107.71	108.27	108.29	108.54	108.38	108.54	106.41
LPI	619.52	805.97	1 243.22	1 366.24	1 436.22	1 615.38	1 698.00	1 794.80	1 893.87	1 969.82	2 206.30	2 334.67	2 456.85	2 558.27	2 633.02	2 709.95	2 762.46	2 848.64	2 207.95

B. ECONOMETRIC METHODOLOGY

The core objective of our analysis is pursued using the hedonic price model, where Holstein semen prices are regressed as a function of traits related to production, physiological and reproduction characteristics. This section will elaborate on the particular attributes used for the analysis in more detail. An assessment of the variables’ relationship with each other, namely correlation issues and how they will be addressed in this study then follows. Consequently, a description of the functional forms considered for the modeling is included.

The hedonic price model does not dictate a particular functional form to follow but rather allows for flexibility (Grafton et al., 2004). However, as the discussion of the data previously explained, the censored nature of the price variable in the series has ruled out linear regression forms from the viable options. The details of the Tobit model chosen to overcome the censored semen prices is explained further in this section. Lastly, empirical methods also consider a Cragg Double-hurdle specification to assess the data between a Tobit and a more generalized specification. A description of this evaluation is described in the last subsection of this methodology review.

1. Defining the Hedonic Model Regression: Explanatory Variables

An initial set up will define the hedonic model as;

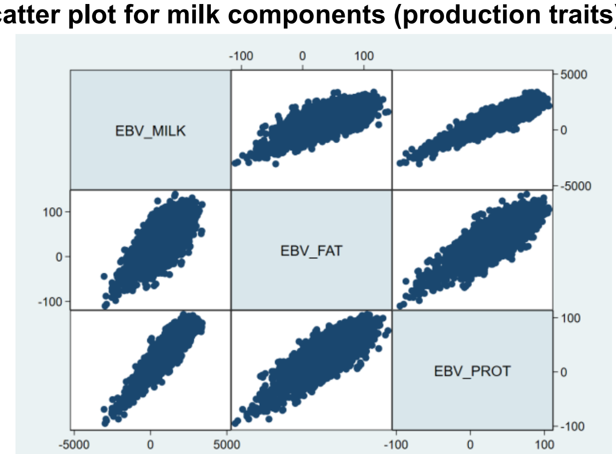
$$SEMENPRICE\ = \alpha + \sum_{i=1..N}^{N} \{\, \beta_i [ATTRIBUTE_i]\, \} + \varepsilon$$

where the semen price (reported in dollars per straw), is described as a function of a constant (α) and the bull attributes highlighted in the literature and available in our database -EBV milk, EBV fat, EBV protein, scores for Feet & Legs, Conformation, Daughter Fertility, Mammary System and SCS -, as well as its error term (ε). The coefficient of the ith bull attribute, β, will denote the monetary value associated to one unit of that attribute in the Canadian dairy semen market.

Milk components

A review of the LPI formulas (see **Chapter 2**) and the last analysis performed on dairy farmer valuation for sire attributes by Richards and Jeffrey (1996) showed that milk has not been included into LPI calculations but it was included in the latter research. A look at the correlation matrix of these milk components showed a high level of association between them, with milk and protein having nearly perfect collinearity. Therefore, as a point of comparison with Richards and Jeffrey's study (1996), the baseline function of the hedonic price regression will include all the three milk components, but additional versions, one including only fat and protein as the LPI function does, and separate ones to only include each individual milk component will be estimated.

Figure 3.2 Correlation scatter plot for milk components (production traits)



Visual representation of correlation factors in **Table 3.3** showing the highly collinear relationship between all milk components. Data sourced from Miglior (2017).

Conformation and Mammary System

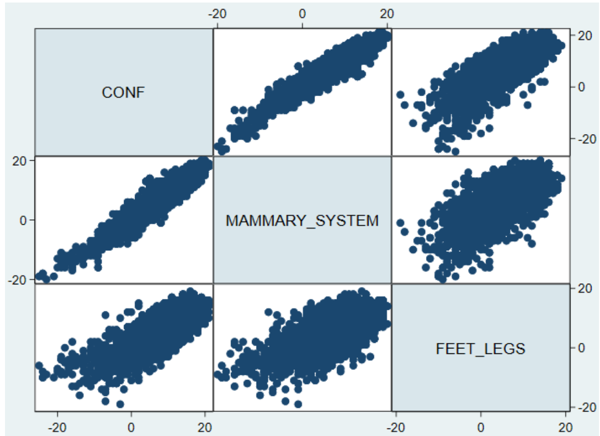
Richards and Jeffrey (1996) reported evidence of synergies "among type categories" in the results, in particular, between body capacity, feet and legs and mammary system. In addition, they noted that the inclusion of "*final class*" into the regression also played a role in diminishing the individual values of the other *type* variables, since final class was a composite category that encompassed the other three (Richards and Jeffrey, 1996). Similarly, the "conformation" variable in our database would share the same component basis as "final class" did for the 1995 data: An assessment of the correlation matrix between conformation, mammary system and feet and legs further confirmed this assertion. In fact, the relationship between conformation and mammary system displayed nearly perfect collinearity.

In both, the LPI formula of 1995 and Richards and Jeffrey's (1996) hedonic price modeling, all three components were included in the explanatory variable set[53]. Industry and the authors still found these components held value in producers' eyes on their own merit: Ultimately, as Richards and Jeffrey (1996) stressed, producers really pay attention to specimens with "a reputation of siring long-lived daughters or that has a package of type traits suggesting problems with feet and legs or the mammary system are not likely to arise." Further, authors recognized that a hedonic price model on bull or semen selection must include "longevity as a major consideration," and since *Feet and Legs* and *Mammary system* may be intertwined, it is necessary to consider both into the equation. Their tobit estimations indeed reported significant marginal values above "their contribution to the conformity of the cow as a whole" (Richards and Jeffrey, 1996).

Although *Feet and Legs* and *Mammary system* are directly related to a herd's *production life* and hence, the operation's profit, *Feet and Legs* could be interpreted as a proxy for longevity (Richards and Jeffrey, 1996), whereas *mammary system* would also hint on the herd's production and udder integrity (resistance to mastitis, lactation capacity) (Harris, 2019). Taking this into account, comparing the results of the model without *conformation* in the set of regressors against an alternative iteration removing *mammary system* and the baseline regression with all the components will also be calculated.

[53] The revised formulas went on to include *conformation* into the equations along with feet and legs and mammary system instead of *final class* (see **Chapter 2, Section C1.2** for LPI formulas).

Figure 3.3 Correlation scatter plot for durability components (Conformation, Mammary system and Feet & Legs traits)



Visual representation of correlation factors in **Table 3.3** showing the extremely high collinearity between conformation and mammary system (corr=0.92), while Feet &Legs displays high collinearity with conformation (corr=0.75). Data sourced from Miglior (2017).

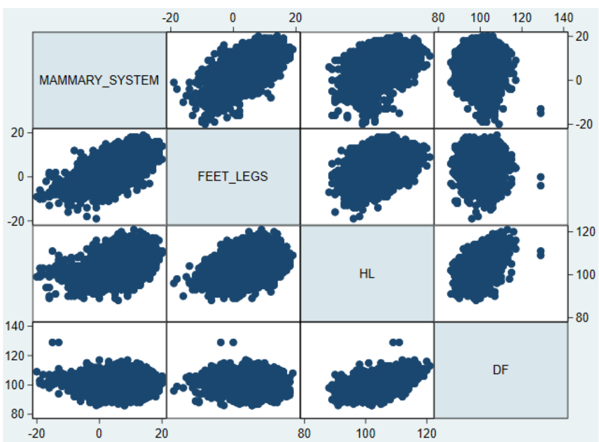
Herd Life and Daughter Fertility

New composite variables like *Herd Life* and *Daughter Fertility* were included in the LPI formula from late 2001 and 2005 onwards, respectively, under the *durability* category (along with the *feet and legs*, *mammary system* and *frame/capacity* attributes) and the *health & fertility* category (along with *Somatic Cell Score*, *Udder depth* and *Milking Speed*), respectively (CDN 2001, 2004; Beavers and Van Doormaal, 2014). Nevertheless, as highlighted in the previous section, Richards and Jeffrey (1996) acknowledged that composite measures like *final class* also posed a challenge to building unbiased models. In their hedonic price methodology, the authors decided to limit the use of attributes to only one per “group of related variables” (Richards and Jeffrey, 1996).

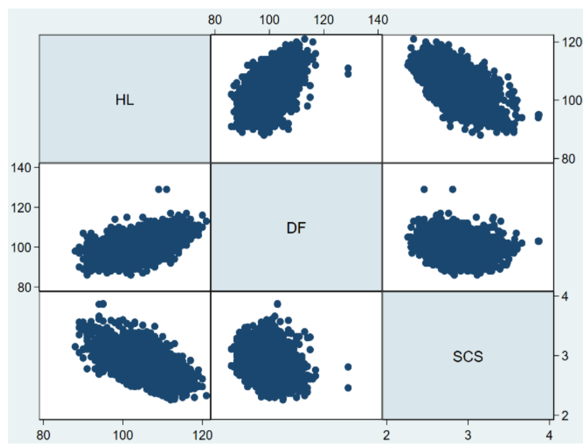
Since our panel series had scores for *Herd Life* and *Daughter Fertility* available, as well as *Somatic Cell Score*, our approach was the following: In the case of *Daughter Fertility*, the measure was a proxy for successful pregnancies carried to term, and was thus considered an indicator for repeatability and a core attribute for breeding decision-making. *Somatic Cell Score*, on the other hand, was highlighted as a crucial indicator for producers on mastitis resistance (Canadian Dairy Network (CDN), 2018), so it was also added into the baseline model of our hedonic price regression. *Herd Life*, however, could be considered an additional longevity attribute, along with feet and legs and mammary system. Consequently, our baseline estimation did not include it into the model. Nevertheless, as the correlation among these variables was assessed, there was no evident tendency towards collinearity with *Herd Life*, such that an additional iteration to consider the significance of this last attribute to producer's *sire* selection will also be included.

Ultimately, studies on Australian dairy producers observed that the most favoured traits for improvement across the entire dairy industry were those related to mastitis, longevity and fertility, while semen fertility and EBV values for production and management were most valued for bull selections across all breeds (Martin-Collado et al., 2015). Similarly, Boettcher and Van Doormaal (1999) asserted that Canadian producers were increasingly paying attention to traits related to longevity and health when making semen purchases or bull selections.

Figure 3.4 Correlation scatter plots for durability components vs. Health and fertility traits; (a) All Durability components vs. Daughter Fertility and; (b) Herd Life vs. Daughter Fertility and Somatic Cell Score (Durability components)



Visual representation of collinearity (see **Table 3.3)** shows high collinearity between mammary system and Feet & Legs (0.62) while Herd Life and Daughter Fertility do not hold these relationships. Data sourced from Miglior (2017).



Visual representation of correlation (see **Table 3.3)** for Herd Life (HL), vs. durability traits shows that the latter do hold a moderate to high degree of correlation with HL (HL and DF corr=0.57, HL and SCS corr= -0.61). Data sourced from Miglior (2017).

Table 3.3 Correlation matrix for key bull traits, 2008-2016, (N=7 739)

	ebv_milk	ebv_fat	ebv_prot	conformation	mamm system	feet_legs	hl	df	scs
ebv_milk	1								
ebv_fat	0.687	1							
ebv_prot	0.888	0.805	1						
conformation	0.434	0.512	0.476	1					
mamm system	0.415	0.478	0.461	0.924	1				
feet_legs	0.313	0.451	0.392	0.752	0.622	1			
hl	0.251	0.382	0.360	0.381	0.471	0.384	1		
df	-0.051	0.071	0.055	-0.071	0.020	-0.003	0.572	1	
scs	-0.167	-0.325	-0.232	-0.292	-0.338	-0.279	-0.610	-0.274	1

2. Functional Forms for Estimating the Hedonic Price Model

As observed previously, in cases where the dependent variable presents bunching of observations at a threshold point, using an OLS model becomes inappropriate, and estimation must turn to a maximum likelihood process (Cameron & Trivedi, 2005; Greene, 2012, 5th ed.). The analysis of the data will begin with a Tobit I model as a baseline -first using annual subsamples of the panel series (nine separate cross-section estimations for each year in the panel series, 2008 to 2016) followed by the estimation across the entire panel series- and finally, move on to a Cragg Double-Hurdle model estimation of the entire bull series. The results from the cross-sectional Tobit I estimations will be used as a reference point to which to compare the last cross-sectional observations from Richards and Jeffrey in 1996, as well as to provide more depth to our first results obtained from the entire panel data collectively.

2.1 Tobit Model estimation

As explained earlier, the true purchase values of a large proportion of semen samples cluster at the zero dollar value, and are unobservable in our database such that, if they were processed under this $5 CDN threshold, the naturally-occurring zeroes cannot be distinguished from the purchases performed under the $5 CDN limit. This, in turn, implies that the observed demand will be underestimating the true or actual demand for the samples across the different bull alternatives (Cameron & Trivedi, 2005, p.531). When there is an observed clustering of values around an extraneously imposed constraint, like the minimum price threshold of $5 CDN in this study, using a Tobit application is the best following mode of action to consider (Burke, 2009; Wooldridge, 2002). Linear approximations to the censored means of semen prices, in this case, using OLS estimation would lead to a flatter slope that is inconsistent with the underlying population parameter (Cameron & Trivedi, 2005, p.531).

A Tobit estimation consists of a hybrid model that will simultaneously run a probit likelihood function for the censored observations while using a normal likelihood distribution for the non-censored observations, and obtain the probability of observing the latent, dependent variable (*L*)

(Verbeek, 2012, 4th ed.). The latent variable is thus maximized with respect to the explanatory coefficient (β), and its standard deviation of the residuals (σ), in the following way;

$$L = \prod_{y_i=0}^{N}\left[1 - \Phi\left(\frac{x_i'\beta}{\sigma}\right)\right] \cdot \prod_{y_i>0}^{N}\frac{1}{\sigma} \cdot \phi\left(\frac{y_i - x_i'\beta}{\sigma}\right)$$

where Φ is the standard normal cumulative distribution function and φ is the standard normal probability density function (Cameron & Trivedi, 2005, p.536). This censored regression model is linear in regressors with an error parameter that is normally distributed and homoskedastic, $\varepsilon \sim N[0, \sigma^2]$(Cameron & Trivedi, 2005, p.536). The marginal effects derived from this regression can be interpreted as the gain (loss) to the maximum present market value of a semen sample from an increment in one of the regressors (i.e. the sire attributes) performance by one unit (Richards and Jeffrey, 1996). The gain of performance will itself relate back to an improvement in genetic factors and thus will signal which trait is most favoured by farmers for genomic technology to focus on.

In summary, a Tobit I model will be used to surpass the bunching of the semen prices at the zero value. Nevertheless, as Cameron and Trivedi (2005, p.538) underscore, the Tobit I model suffers from a "heavy reliance on distributional assumptions. If the error is either heteroskedastic or nonnormal, the MLE is inconsistent." In addition, the model assumes that the marginal effect of the variables is the same magnitude and direction (sign) for the probability of consumption as on the expected level of consumption (Burke, 2009; Wan & Hu, 2012). In this case, the marginal effects of the bull trait variables have the same magnitude and direction for both, the probability of purchasing bull semen (yes or no), as for the expected amount of Holstein semen to be purchased (number of semen doses given that producer decided to participate in the semen purchasing '*event*').

A Cragg double-hurdle model will also be employed to explore the effect of the attributes on the price of semen under a functional form that will relax the imposed assumption in the Tobit model that restricts the coefficients of the explanatory variables to be the same in both, a participatory stage and an intensity stage (i.e. only one 'event' occurs and not two) (Greene, 2012, 5th ed.). The Cragg Double Hurdle Model is also called a two-part model because, unlike the Tobit, which considers both stages a single event, it allows for these stages to be assessed separately, an initial selection into the event (e.g. buying a semen straw) and the following intensity stage (e.g. how many straws are purchased), and the estimators' effects can now move in different directions and magnitudes under this formulation (Verbeek, 2012, 4th ed.; Burke, 2009; Cameron & Trivedi, 2005; Greene, 2012, 5th ed.).

2.2 Cragg Double Hurdle Model

Corner solution models were designed to address situations where a dependent variable would appear to pile up or bunch at a particular value, while remaining continuous in its other explanatory variables (Burke, 2009). Cragg proposed this approach in 1971, to deal with expenditure models "with excess zeros" (Cameron & Trivedi, 2005, p.546), particularly in agricultural production cases and input demands (Burke, 2009). A double hurdle model examines the likelihood of participation in the event and the intensity of participation or degree of consumption for a good Y* (Greene, 2012, 5th ed.). Duan et al. (1983), for instance, used this approach to forecast medical expenses, where the first hurdle was incurring in medical expenses in a year, while the second hurdle was the intensity of the expenses, conditional on expenses having occurred for that year. Rather than collapsing them into one effect, the Double Hurdle Model assumes that the determination processes are different, and separates the decision to participate from the decision of how much to consume a specific good (Burke, 2009). Contrastingly, in a Tobit specification, the effects of the explanatory variables on the dependent variable *Y*, are assumed to be of the same magnitude; all the clustered observations as well as the rest of the non-clustered, non-limit observations, will have the same impact on the dependent variable *Y* (Greene, 2012, 5th ed.; Burke, 2009). Therefore, as Cameron and Trivedi (2005, p.545) explain, "a two-part model that permits the zeros and non-zeros to be generated by different densities adds flexibility [from the assumptions of the general Tobit I model]." Using a binary indicator variable, *d*, where *d*=1 for participants and *d*=0 for non-participants (Cameron & Trivedi, 2005, p.533, 545):

$$f(Y^*|x) = \begin{cases} P\,(d = 0 \mid x), & if\ Y^* = 0 \\ P(d = 1 \mid x)\, f(Y^*|d = 1, x), & if\ Y^* > 0 \end{cases}$$

More specifically, this two-part model uses a probit specification for the clustered observations to examine the probability of participating in the event, while the non-limit observations are used to estimate a linear regression to study the behaviour of active consumers (as these transactions already imply participating into the event or consumption of the good);

$$Y = \prod_{y_i=0}^{N}\left[1-\Phi\left(\frac{x_i{}'\gamma}{\sigma}\right)\right]\prod_{y_i>0}^{N}\frac{1}{\sigma}\cdot\phi\left(\frac{y_i - x_i{}'\gamma}{\sigma}\right)$$

$$ln\,Y = \sum_{y_i=0}^{N} ln\left[1-\Phi\left(\frac{x_i{}'\beta}{\sigma}\right)\right] + \sum_{y_i>0}^{N} ln\left[\frac{1}{\sigma}\cdot\phi\left(\frac{y_i - x_i{}'\beta}{\sigma}\right)\right]$$

Where the two-step model collapses into the Tobit I regression if the estimator in the first hurdle, $\boldsymbol{\gamma}$, does not vary from the effect observed in the log likelihood for the non-limit observations, such that $\boldsymbol{\gamma}=\boldsymbol{\beta}/\boldsymbol{\sigma}$. (Greene, 2012, 5th ed.; Burke, 2009).

Although the modelling separates the sample into two treatments, the estimation is performed jointly, so that the likelihood function will still be defined over the entire sample, even if it follows a truncated normal distribution (Cameron & Trivedi, 2005, p.545). Ultimately, this two-step process allows researchers to study the effect of the explanatory variables on the event or good (Y) conditional on it already having occurred, i.e. participation is already confirmed (P (d*=1) (Burke, 2009; Cameron & Trivedi, 2005).

In this study, postive semen prices will be used as the indicator for the first participation hurdle (i.e. *d*=semen bought), where anything other than zero would indicate a transaction occurred (*d*=1), while the second hurdle of the estimation will be run using the price for semen as the dependent variable (i.e. *f* (*SEMENPRICE* **|** semenbought=1, x); the attributes associated with each bull described above will be used as explanatory variables across both components of the Cragg double hurdle estimation (*x*=sire attributes).

3. Regression Setup for the Separate Model Iterations

Each of the model specifications chosen to analyze the data, Tobit and Double-Hurdle, will consist of a general regression that considers the entirety of the time panel data. Ultimately, this analysis will run under the assumption that the unbalanced nature of the panel series is not deliberate and, thus, the models' restrictions on the latent variable still hold.

In addition, individual, annual, cross-sectional iterations for each of the time periods will be run separately to notice any change in farmers' bull-selecting behaviour for bull attributes throughout the time periods. Evaluating a change in the values of the estimators year by year will help to discern if there is indeed a change in behaviour patterns for bull selection over time, particularly after the introduction of genomic selection into Canada, as claimed by the Canadian Dairy Network (Beavers and Van Doormaal, 2015).

C. EXPECTED RESULTS

In regards to the impact of the LPI in farmer's sire selection decisions, we would expect to see the results from the hedonic modelling to match the order of importance conferred to them by the weights of the LPI formula. Similarly, if the LPI system effected a significant impact in producers' transaction decisions, we would expect to see a heavier emphasis on conformation, milk fat and protein at the latter end of the time periods, namely from August 2015 onwards. Further, we will evaluate if there was a variation in the degree of importance that the main attributes had in producers' selection decisions, starting with mostly production-based attributes -namely the milk components first, followed by conformation, and a measure of repeatability (number of daughters) - as Richards and Jeffrey (1996) concluded in their research, shifting towards a set of traits favoring traits related to longevity and health like Boettcher and Van Doormaal had noted in 1999 and Martin-Collado et al. (2015) had confirmed on their assessment of the general dairy producer base in Australia, or if their preference structure remained close to the milk components and conformation as encouraged by the LPI's formula. In terms of the econometric methods being employed, we strive to improve the fit of the data to a model that can best describe Canadian producers' semen selection process: The distribution of the semen prices hint to the possibility that a two-step model might be better equipped to predict producers' decision to participate in a semen transaction and then the extent to which they decide to take part in the market. If this is the case, we would expect to see different values for the attributes' coefficients for each stage, and varying marginal effects between the Tobit I and Double-Hurdle models.

The main objective of this thesis is to reassess the sire-selection decision after the introduction of genomic technologies into the national semen market. The purpose is two-fold: Firstly, the aim is to identify any changes in sire attribute preference through time across the Canadian farmer population. Secondly, the attribute preference relationships can better link farmer decision patterns from real market transactions than an analysis in change rates of bull attributes using statistical correlations, and be further fed back to the development of selection indices like the LPI. New considerations in this study include the addition of varieties and another MLE approach to characterize the farmer's decision-making process. The econometric applications hold promise in better delineating the decision-making process based on the market data.

Ultimately, this thesis strives to characterize the current values conferred to key sire attributes during farmers' planning process for breeding new heifers. The findings of this study can support industry efforts to encourage increased sire selection through the use of genomic technologies by informing breeders about the main attributes to focus on improving with this technology, or for policymakers to explore the promotion of different attributes through education outreach or support systems.

Chapter 4 . ANALYSIS OF RESULTS AND DISCUSSION

A. OUTLINE OF CHAPTER

In this chapter, the analysis of the changes in bull attribute valuation by farmers when selecting semen to purchase before and after the increased use of genomics in dairy genetics in 2008 happened. As explained in the third chapter, this main objective is pursued by comparing cross-section data for the years of 1995, 2000, 2005 and 2008 published by Holstein Canada, to highlight traits of interest prior to the use of genomics, and subsequently, by modeling Canadian semen price data from aggregate transaction records of Holstein semen purchases between 2008 and 2016 in Canada. Semen prices from 2008 onwards were regressed as a function of the key bull attributes identified in the literature and available in the bull proof data to obtain the implied value of each trait over the period of 2008 to 2016 by the average Canadian farmer. Lastly, the results obtained from hedonic price modelling served for the third and final objective; comparing the preference ordering implied by the weights set up in the LPI formula to the ranking revealed by the econometric estimations (hedonic price models). A presentation of the results, their interpretation in the context of the Canadian semen market and their implications for the use of genomics in breeding efforts as well as for the study of farmer behaviour can be found in this chapter. Further extensions of the findings and other considerations will be discussed in the next and final chapter.

B. OBJECTIVE 1: ASSESSING THE VARIATION IN ATTRIBUTE VALUATION OVER TIME

In order to appreciate the state of the Canadian dairy industry and the fluctuations in the average sire profile prior to the rise of genomics in 2008, historical bull proof records from Holstein Canada publications were collected (Holstein Canada, 1995; 2000; 2005; 2008). This study used four annual publications in total, starting from the year where the last hedonic price study on farmer trait preference was conducted, 1995 (Richards and Jeffrey, 1995), and then using three more records from 2000, 2005, and 2008, when the use of genomics began in selection breeding (Beavers and Van Doormaal, 2015; Taylor et al., 2016). The first objective of this study thus set out to evaluate the trends observed across the average scores of the key sire attributes for the entire Holstein bull registry available in Holstein Canada's annual publications and establish the background context before genomics took a major role in sire breeding.

1. Historical Holstein Proof Data

In the previous chapter, the descriptive statistics for the majority of traits in the Holstein bull proof records were reported. In this discussion, we elaborate on the differences observed between two pools of the same Holstein data, the overall sire records (the complete series) and the top 100 LPI-ranking sires, over different years examined (1995, 2000, 2005 and 2008). The aim of this evaluation is to identify changes in the traits' importance over time, as well as to assess if there are observable differences in the variation levels of certain traits between the top ranking bulls and the general bull population. Ultimately, with this endeavor, we wish to reconcile the last econometric study on Canadian dairy by Richards and Jeffrey (1996) and the latest statistical studies of the industry and use it as the basis of comparison for our econometric analysis starting with 2008 data. Further estimations of this data for the individual traits in this period using a hedonic regression is beyond the limits of this study since no price data was available to match the bull proof records from Holstein Canada's publications.

1.1 Comparing the total registered sires' average to the Top 100 LPI-ranking bull's average within the same year

In addition to the descriptive statistics for each of the selected annual publications of the registered Holstein sires, our analysis gathered statistics for a subsample of the entire pool, the top-100 ranking bulls according to their LPI, and compared their individual trait score averages to the complete pool of registered sires (see **Table 4.1**). Averages for key traits, such as milk yield, protein and fat content, mammary system, feet and legs, conformation, herd life, somatic cell score (SCS) and daughter fertility were used as representative attributes for each main category found in the LPI formula (production, durability, health and fertility)[1]. While the weight of each category changed over time, this breakdown in the general LPI formula is still the same[54]. Similarly, the measurement system for

[54] **General LPI Formula:** ([Emphasis$_i$ • Factor$_j$] [Production Component + Durability Component + Health & Fert.] + Constant), where the emphasis and factor values change according to the component categories. (See Chapter 2, **Table 2.1**)

the different traits used estimated breeding values (EBVs)[55] in the 2000 publication onwards, such that the scores were calculated based on a moving average, that is, a mean for the population that was updated annually (a brief description of each trait is available in **Appendix 3**). Nevertheless, as **Table 4.1** attests, the scores in 1995 used very different scaling, Breed Class Averages (BCA), and thus prohibited any further comparison.

In broad terms, the mean scores between both groups showed a pronounced advantage by the top-100 LPI-ranking bulls over the general sire pool in each of the annual publications considered in this study. Moreover, the largest difference among the overall sample averages and the top-ranking subsample's averages was observed in the milk component scores. In particular, 1995 stood out from the other years with the most marked gap between the general average scores and the top-ranked sires. The remaining year periods (2000, 2005 and 2008), on the other hand, observed a similar magnitude in the difference among the average scores of traits like *mammary system* (top-ranking avg was 58.42% greater than overall sire avg in 2000, versus 58.36% in 2005, and 40.05% in 2008), *somatic cell score* (top-ranking bulls score was 3.2% lower than overall sire avg., versus 3.17% lower in 2005 and 1.64% lower in 2008) and *herd life* (top-ranking avg was 3.4% greater than the avg of the total sire pool in 2000, versus 2.08% advantage in 2005 and 1.04% in 2008) for the top-100 ranking sires and their general sire averages, for instance.

In 1995, the top 100 LPI-ranking bulls produced almost three times as much of these milk components than the average bull in Canada (2.77, 2.67 and 2.8 times as much milk, fat and protein, respectively, than the average bull from the general population [composed of the entire bull registry, including the top ranking bulls]). Over the next years, however, average scores for the three milk components - milk, fat and protein- did not differ as drastically between an average bull and a top-100 LPI bull. In 2000, for instance, top LPI-scoring bulls were only 1.5 times more productive in milk component values as the average bull (1.38 times for milk, 1.43 times for fat, 1.45 times for protein). Similarly, 2005 and 2008 saw a comparable range difference to the data from 2000, although the fat average of the top 100 LPI-ranking bulls was slightly above the other two components in terms of

[55] **Estimated Breeding Values** (EBVs) are "a value which expresses the difference (+ or -) between an individual animal and the herd or breed benchmark to which the animal is being compared. EBVs are reported in terms of actual product e.g. days, kg of weight or mm of fat depth, etc." (The Cattle Site, 2011).

difference than the general bull average (top LPI-ranking bulls produced 1.37 times more milk, 1.74 times more fat and 1.43 times more protein in 2005, whereas in 2008, the top LPI-scoring bulls produced 1.58 times more *milk*, 1.78 times more *fat*, 1.67 more *protein*). While the data suggests an improvement in the average performance of Holstein bulls' offspring for milk components across time, it is not possible to conclusively identify a trend using only selected data over a thirteen-year period.

The rest of the key attributes also registered higher averages for each year among the top 100 LPI-scoring bulls than those of the general sire pool, with *feet and legs*[56] having the second-highest gap, then followed by *dairy character*[57], then *conformation*[58], *mammary system*[59], and finally, *capacity*[60]. *Somatic cell score (SCS)*, on the other hand, was only measured starting 2000 and had negligible differences among the two sire samples, although the top-scoring bulls' average was slightly lower than the general bulls' average. The significance in these observed discrepancies between the top 100-ranked sires and the overall sire pool for each year period is two-fold. Firstly, it brings to light the fact that the top-producing sires are experiencing consistently higher improvements in their attributes than the average sire in Canada. Secondly, it suggests that, for top-ranking sires, milk components have taken the lead in the priority list of attributes to enhance, with *feet and legs* a close second, later followed by *dairy character*, and then *conformation* and *mammary system*. *Somatic cell score*, according to these variations among the top LPI-ranking bulls and the general

[56] 1995 average for the top 100-ranking bulls was 194.88% higher than the general average; 2000 average was 72.89%; 2005 only had a 26.46% difference between both of the average values, such that feet and legs was the fourth attribute in terms of discrepancies among the means for the overall bull pool and the top-ranking bulls; 2008 had a 40.05% difference between these bull samples.

[57] 1995: Average for top-ranking bulls was 135.31% higher than that for the entire sample; 2000: top-ranking bulls had a mean 57.54% higher than the overall sample; 2005: 28.71% variation between means, with the top-ranking bull mean being greater; 2008: Temperament variation between both means was negligible, with top-ranking bulls having a 1.61% higher mean (dairy character n/a)

[58] 1995: Final class mean of top-ranked bulls was 100% above the overall mean (Conformation was n/a); 2000: mean of top-ranked bulls was 60.36% higher than the overall mean; 2005: top-ranked bulls had an average 40.72% higher than the general average. Conformation was the second-highest difference among the average bull and the mean top-ranking bull for 2005. 2008: the top-ranked bulls had a 21.37% greater average than the general pool

[59] 1995: Mean for top-ranking bulls was 81.52% greater than that of the overall bull sample; 2000 and 2005: The mean variation was practically identical - 58.42% and 58.36%, respectively - with top-ranking bulls also faring higher than the average bull sample; 2008: top-ranking bulls had an average 40.35% higher than that of the general bull sample

[60] 1995: Top-ranked bulls' average was 46.62% higher than the general sample's; 2000: Top-ranking bulls had an average 43.22% greater than the general sample's; 2005: top-ranked bulls saw their mean shrink by 3.61% from the general population mean; 2008 stopped recording capacity values

bull pool, is showing virtually no change among the two averages, which would suggest that it had not been affected through the existing breeding techniques as much as the other traits.

These two implications resonate with similar diagnoses of the Canadian Holstein population. Strictly based on the differences in average scores, the narrative made in Richards and Jeffrey's (1996) hedonic estimation, which portrays Canadian dairy producers as mainly production-focused, would align with the greater gap in the mean scores we observed for the milk components, where the top-100 bulls outpaced the average bull from 1995 up to 2008. Additionally, a study by CDN (Beavers and Van Doormaal, 2015) involving 193, 700 cows from 2, 500 herds nationwide also noticed that herds in the top 10 percent for LPI gains achieved improvements in their traits "at a much faster rate than others" (Beavers and Van Doormaal, 2015). More specifically, the annual genetic gain for the top 10% LPI-ranked herds saw a gain on the production-related attributes (protein and fat) that was 72% greater than the annual progress for the average herd (Beavers and Van Doormaal, 2015). Similarly, the study found the highest discrepancy among milk component trait gains was in protein, followed by milk content and lastly, fat (81.5%, 80.5% and 66.7%; Beavers and Van Doormaal, 2015).

In addition, the fact that *feet and legs* would closely follow the largest discrepancy in mean scores would fit Boettcher and Van Doormaal's (1999) assertion of the industry's growing interest in functional traits for their bull selection decisions. Furthermore, the results reflect an increased effort in recovering ground on cow health, as explained in Miglior et al.'s (2017) review of the dairy industry. Moreover, the average score gap between the national population mean and the top-ranked mean supports Miglior et al.'s (2017) assertion that the focus in production traits and the antagonistic relationship between yield and health traits produced a lag in overall cattle health, which ultimately "brought attention to genetic selection for improved health" to the forefront (Miglior et al., 2017, p. 10260).

Similarly, the average annual progress rate in the last 5 year period of the CDN's study also demonstrated that the largest gap between the average gains from the average herd and the top 10% herds was observed in the Health and Fertility components of the LPI, since the top 10% gain was 450% above that of the average herd (0.9 annual gain vs -0.2 annual gain) (Beavers and Van Doormaal, 2015). Nevertheless, given negative rate of annual change in the Health and Fertility component of the country's average herd, Beavers and Van Doormaal (2015) deemed most of

Canadian dairy operations had “virtually made no genetic progress for this component while the best herds have achieved an average gain of 1 point per year during the last five years.” In this present study, the negligible discrepancy over the years for the mean values of *somatic cell score* and *daughter fertility* in the Holstein proof publications also align with the average herds’ progress over time from the CDN (Beavers and Van Doormaal, 2015). However, the stark difference found by the CDN’s herd study (Beavers and Van Doormaal, 2015) in terms of gains on these Health and Fertility components for the top 10% herds and the average herds, does not parallel the menial gap found in our analysis of the average sire registry and the top 100-ranked sires for these traits (*somatic cell score* and *daughter fertility*). Instead, methodology discrepancies in data collection may be at play in this case. While the CDN study was able to maintain records of the same cows and herds for their study, the records of sire totals by Holstein Canada not only varied across publications, “but also, the low quality of the data, which represents an issue in the analyses of reproduction data” could have played a factor in the diverging observations (Miglior et al., 2017). In addition, variability in phenotypic responses by different bulls, compounded with different management strategies, and the slow to medium heritability of health and fertility traits (Miglior et al., 2017), could also have had a role in the contrasting observations.

Finally, Beavers and Van Doormaal (2015) signalled that the annual score gains showed an overall, “significant progress is made for conformation, even if progress for LPI is minimal,” since all their herd groups (bottom 10%, average herd, top 10%) saw comparable gains per year on this attribute. More specifically, this CDN herd study showed the average score progress per year for the top 10 % herds was 20% greater than the average herd gains, and 40% greater than the bottom 10% herds (Beavers and Van Doormaal, 2015). In turn, the selected Holstein proof data from 1995 to 2008 in our study showed larger discrepancies among average confirmation scores in the earlier years - with the top 100 bull mean score being 60% and 40% greater than the average bull in 2000 and 2005, respectively- but showed a similar discrepancy to the CDN’s most recent analysis between the average bull and the top 100 bull mean values for confirmation in 2008 of 21% (Beavers and Van Doormaal, 2015). Once again, the variations among these groups could speak to the change in selection strategies from solely production-focused to a more holistic approach: Conformation was used as an indicator of longevity and fertility, as farmers ultimately aimed to cut down on operation costs as well (Miglior et al., 2017). Therefore, while the greatest gap between the average sire pool and the top-ranked sires relates to production traits, it was traits like *feet and legs*[55] and *dairy character*[56], *conformation*[57] and *mammary system*[58] where the largest gains were observed. The differences in these durability and health-related traits highlighted in our comparative analysis align with the notion that Canadian farmers also began to pursue a more holistic approach in their selection process at the turn of the century.

Overall, both the top-ranking LPI bulls and the general bull population observed gains in their performance over time, as the next section will discuss, but in general, the gaps in scores decreased in magnitude over the years between the top-ranking sire and the overall sire population. The reduction in the magnitude of growth between the top-ranking bulls and the general bull database shows the performance and condition of the national herd improved across time, and the gap between the top sire and the average bull shortened in 2008, compared to 2000 conditions. Nevertheless, without price data associating the different bull traits to farmers, it is impossible to find whether or not the valuation of individual traits changed across time. Ultimately, these comparisons show that there is some convergence across time between the general population and the top 100 by LPI score, where the general population of bulls used improved over this period.

1.2 Calculating variations in averages across years

In an effort to better understand the variation patterns in the national dairy herd prior to the deployment of genomic selection in breeding programs in 2008, we compared the average scores over the different years (2000, 2005 and 2008) for the overall sire population against the top-100 LPI ranking bulls. Understanding the extent of discrepancy in sire performance allows us to better understand the priorities in breeding selection for the average Canadian farmer as well as the top-producing (usually more risk-tolerant) producers. Ultimately, our evaluation of the statistical data suggest that both groups shifted away from production traits.

a) Variations over time for the annual sire registry pool

Changes in mean scores across the different bull traits showed a wide fluctuation over the years. Among the overall population averages, the largest variations observed were on *dairy character* scores of 2000 to 2005 and *mammary system* from 2005 to 2008 (increases of 24.95% and 22.8%, respectively), even though the variation for *mammary system* between 2000 and 2005 was among the least drastic, along with *protein*'s (1.38% for *mammary system*; 1.32% for *protein*)[61]. *feet and legs* held the second spot in terms of highest score gains, for both the 2000 to 2005 and the 2005 to 2008 comparisons. Moreover, the magnitudes were similar for both periods; rising by 14.05% from 2000 to 2005 and 14.71% from 2005 to 2008. *Conformation* then stood out as the following trait with the largest positive change; its mean rising by 9.13% in the 2005 score compared to 2000, and by 13.83% in 2008 from 2005's score. Lastly, the values for *milk* and *fat* volumes had the smallest changes, with *milk* observing a gain of 5.41% in average yield values between 2000 and 2005, but falling by 1.54% between 2005 and 2008, and *fat* rising by 3.63% and 2.55% in the same periods[62]. *Somatic cell score* had negligible changes over the time period assessed, so it was not considered significant against the other score variations[63].

Ultimately, this comparative estimation shows that the ranking of traits based on their average score variations changed on the two 5-year period comparisons available from our dataset. Despite the fact that the actual traits holding the top spots in terms of greatest gains in a 5-year period did not remain the same between 2000 to 2005 or 2005 to 2008, neither within the overall sire pool averages or within the top 100 LPI-ranking bulls, the comparison did show that the top three traits in both periods were related to the Durability category of the LPI formula, with *Mammary System*, *Feet and Legs* and *Conformation* ranking among those positions (see **Table 4.2**). These observations corroborate Miglior et al.'s (2017, p. 10257) assessment of the dairy industry having

[61] Protein variation here refers to the change in yield volumes as per the 2-year average of kilograms produced on **Table 4.1**.
Dairy character reporting was replaced by Temperament in 2008, under a different measurement scale, and thus prevented any comparison between 2005 and 2008 mean values.

[62] *Capacity* saw a rise of 4.1% in 2005 from 2000's score and held 4th place among the main key traits assessed in the annual proofs, but the measure was discontinued in 2008 so a comparison between 2005 and 2008 was not possible.

[63] Overall sire pool average rose by 1.13% in 2005 from 2000 score average and dropped by 0.4% in 2008 compared to 2005. The top 100-ranking sire average dropped by 1.49% in 2005 from 2000, but rose by 1.17% in 2008 compared to 2005.

"a shift of selection emphasis in the last decade from mainly production to functional traits associated with health and fertility."

In contrast to Richards and Jeffrey's (1996) depiction of sire selection in Canada in 1995 as production-focused, the score gains in average values for the general sire pools in the Holstein registry hint to a move away from selecting bulls solely on production traits (i.e. milk yield, fat and protein content). Studies on Australian dairy farmer typologies also found Holstein farmers "were more prone to be classified as type focused," and thus favour traits like mammary system, longevity and mastitis resistance (analogous to SCS) the most (Martin-Collado et al., 2015, p. 4157). Further, while Beavers and Van Doormaal (2015) noted that "most of the annual rate of gain in LPI comes from progress for production and durability" in their study of Canadian herds[64], most of what we observe in our analysis of Holstein proofs is that attributes belonging to the durability category of the LPI formula had the biggest positive score variations on these years (i.e. *feet and legs*, *mammary system* and *herd life*). Consequently, our results imply that the emphasis on durability characteristics in the LPI is misaligned from the average farmer's preference structure (since production was given priority at 51 percent of the LPI formula in 2008 while the weight for durability was only 34 percent in the same year).

In addition, values for the different milk components' EBV scores also decreased over time, even though the ME 2 year average production of these experienced gains for both, the overall sire pool and the top-100 ranked bulls. Although the effect of genomic selection had not taken off prior to 2008, a rise in the volumes of the milk components is observed across these periods. The decreasing EBV average values could thus speak to the closing gap in the production margins of the registered sires, as more of the lower-producing sires, and least efficient farms, exited the semen and dairy markets. A resulting increase in the average performance value would thus yield a smaller difference (estimated yearly), between an animal's performance and the average performance (since EBV work with moving averages). A reduced EBV difference between an individual's performance and the average pool performance also reflects the genetic improvements

[64] More specifically, production-related traits represented 57 percent of the LPI gains in average herds, while it accounted for 62% of the top 10% LPI-ranking herds.

across Canadian herds and potential homogenization of production capacity among the remaining breeding sire specimens.

In contrast, Beavers and Van Doormaal's (2015) herd study with the CDN followed the same cows and herds to compare genetic gains over five and ten year periods, such that, in addition to the individual cows and management techniques remaining the same, their point of comparison also remained fixed on the starting year average performance when estimating EBV values. Once again, the difference in methodology calls for caution in the extent to which the observations can be comparable for interpretation. Lastly, Miglior et al. (2017) point out that the opposing genetic correlations between fertility and milk yield will inevitably be at odds when pushing for greater individual performance of these traits and should be factored in the breeding considerations. The observed EBV decreases over time in our analysis of the Holstein sire proof scores, along with the increases in durability components, would reflect farmers' desire for a more sturdy dairy herd in durability and longevity aspects, even if it entailed an average loss of 15% in milk component productivity. Similar reductions in the mean EBV milk scores of the top 100 sires and gains in durability-trait values further support this forming preference pattern.

b) Variations over time for the top 100-ranking bulls

The variations across the top 100 LPI-ranking bulls showed a very different trajectory in terms of gains and the specific traits (see **Table 4.2**). These scores saw drops among most of the traits over the time period considered. *Fat,* for instance, although rising 1.57% in 2005 from 2000 EBV values, dropped by 16.43% in 2008 from its 2005 mean score. Similarly, while *Mammary System* dropped by 1.34% in 2005 from 2000 values, it gained 9% on its 2008 mean from 2005. *Dairy character* dropped by 15.88% in 2000 compared to 1995, but gained 2.1% in 2005 versus 2000 values. Consequently, *Conformation* registered the smallest drop in 2008 scores against 2005 values (1.82% loss), and third smallest in 2005 from 2000 scores (4.24% loss). Once again, 1995 was omitted from the analysis due to the different measurement basis used to score traits.

Unlike the general sire pool, the top 100 ranking pool observed almost no change in EBV scores for Milk and Protein from 2005 to 2008. *Protein* was the second smallest drop in 2008 (shrunk by 0.32% from 2005 average score) as well as for 2005 when compared to 2000, although the loss was much larger (16.29% loss). Similarly, *Milk* was fourth in terms of losses for 2000 to 2005 mean values (17.57% drop) but gained only 0.54% in its average score in 2008 compared to 2005. On the other hand, *Feet and Legs* saw a significant gain of 27.04% in 2008 when compared to 2005, although it experienced a loss of 16.58% in its 2005 mean score compared to 2000's. *Somatic cell score* EBV values and *dairy character* had negligible variations. Solely based on the mean value variation, we are unable to discern if the negligible changes in health values like these would be due to low interest from farmers or to the poor observable gains from their selection efforts due to low genetic heritability.

Ultimately, the increase in LPI values over time from 2000 to 2008 cannot be attributed to a rising trend in the production components, since all the EBV scores for the milk components had net drops over the time period, contrary to Beavers and Van Doormaal's (2015) findings on herd progress. Instead, the results hint, once more, to durability components playing a greater role in LPI values during this period than that accounted for in the LPI formula[65]. Considering the genetic correlations of yield traits against fertility, conformation and longevity traits, the low and moderate heritability of these (Miglior et al., 2017), and the sizeable gains in *feet and legs* and in *mammary system* scores of 2008 do, in fact, match with the observed "shift of selection emphasis in the last decade from mainly production to functional traits associated with health and fertility" by Miglior et al. (2017, p. 10257). Furthermore, the drop in EBV milk yield values could be reflecting the trade-off of higher milk yields for stronger health and fertility values. Similarly, the mean score falls of these traits could also be a result of achieving a greater mean yield performance across the sire pool (used as the point of reference in EBV calculations). Lastly, these greater gains in durability-type traits such as *feet and legs* and *mammary system* of the top 100 ranking bulls would also fit Roger's theory of innovation pattern (2003, 5th ed.), where the most informed, risk-taking producers will adopt different strategies and technologies first, influencing an early adopter group into changing assigned values to bull traits until it gains critical mass across all the industry.

[65] Durability components include *Feet & Legs*, *Mammary System*, *Herd Life* and *Frame/Capacity* (2005). The 2005 LPI formula weighed the durability category at 36 percent, while the 2008 formula weight diminished to 34 percent in favour of the production category at 54 and 51 percent, respectively. The LPI formula of 2000 weight for production-related traits (fat and protein content) was 8 versus the 4 conferred to durability-related traits (full formulas displayed in **Chapter 2, Section C. 1.2**).

Table 4.1 Average score values for annual proof records of registered sires in Canada, 1995, 2000, 2005, 2008: Comparison between the total sire pool and the Top 100 LPI-ranking sires

	1995	TOP100 ('95)	2000	TOP 100 ('00)	2005	TOP100('05)	2008	TOP 100 ('08)
MILK	5.547	15.34	1185.867	1635.354	983.829	1348.1	859.522	1355.44
FAT	5.71	15.260	40.607	58.020	33.864	58.93	27.739	49.25
PROTEIN	5.892	16.6	38.675	55.929	32.803	46.82	27.994	46.67
2yr avg Milk kg	7247.544	7953.697	-	-	-	-	-	-
ME Milk kg	-	-	10519.97	10966.830	11089.17	12193.67	10918.26	11120.21
2yr avg Fat kg	269.103	297.030	-	-	-	-	-	-
ME Fat kg	-	-	383.756	401.879	397.683	410.4	407.842	423.4
2yr avg Prot kg	230.535	255.707	-	-	-	-	-	-
ME Protein kg	-	-	334.905	347.919	339.34	345.43	344.663	356.9
Final Class/CF	2.867	5.75	-	-	-	-	-	-
CONF	-	-	5.379	8.626	5.87	8.26	6.6821	8.11
LPI	460.254	1272.82	1023.673	1600.465	951.207	1631.22	977.219	1696.99
ETA Capacity	1.984	2.909	-	-	-	-	-	-
Frame/capacity	-	-	3.061	4.384	3.185	3.07	-	-
ETA Feet Legs	1.497	4.404	3.231	5.586	3.685	4.66	4.227	5.92
ETA Mamm. S	2.749	4.990	4.846	7.677	4.913	7.78	6.042	8.48
No daus class'd	255.881	411.727	-	-	-	-	-	-
SCS	-	-	2.9703	2.953	3.004	2.9089	2.992	2.943
HL	-	-	3.088	3.193	3.037	3.1001	102.352	103.42
Dairy char.	3.563	8.384	4.477	7.053	5.594	7.2	-	-
Temperament	-	-	-	-	-	-	97.916	99.49
DF fertility	-	-	-	-	-	-	98.368	99.37
ET births*	1134/1610		576/759		348/426		392/475	
ET %	70.43		75.89		81.69		82.53	
Total bulls	1610	100	759	100	426	100	475	100

*ET: Embryo Transfer; Number of bulls bred by ET vs. total bulls in registry

Table 4.2 Ranking in average score fluctuation for Holstein Canada proof data for the overall sire pool and the Top 100 LPI-ranking sires

Overall Sire Pool			Top 100 LPI-ranking Sires		
95-00	**00-05**	**05-08**	**95-00**	**00-05**	**05-08**
1. Mammary system (76.28%) [Durability]	1. Dairy character (24.95%)	1. Mammary system (22.98%) [Durability]	1. Mammary system (53.85% [Durability]	1. Milk* (11.19%) [Production]	1. Feet & Legs (27.04%) [Durability]
2. Dairy character (25.65%)	2. Feet & Legs (14.05) [Durability]	2. Feet & Legs (14.71%) [Durability]	2. Feet & Legs (26.84%) [Durability]	2. Fat* (2.12%) [Production]	2. Mammary system (9%) [Durability]
**Feet & Legs (115.83%) [Durability]	3. Conformation (9.13%) ~[Durability]	3. Conformation (13.83%) ~[Durability]	3. Dairy character (-15.88%)	3. Dairy character (2.08%)	3. Protein* (3.32%) [Production]
	4. Milk* (5.41%) [~Production]	4. Fat* (2.55%) [Production]		4. Mammary system (1.34%) [Durability]	4. Fat* (3.17%) [Production]
	5. Capacity (4.05%) [Durability]	5. Protein* (1.57%) [Production]		5. Protein* (-0.72%) [Production]	5. Conformation (-1.82%) ~[Durability]
	6. Fat* (3.63%) [Production]	6. Milk* (-1.54%) [~Production]		6. Conformation (-4.24%) [Durability]	6. Milk* (-8.80%) ~[Production]
	7. Mammary system (1.38%) [Durability]			7. Feet & Legs (-16.58%) [Durability]	
	8. Protein* (1.32%) [Production]			8. Capacity (-29.97%) [Durability]	

*Variation percentages for the different milk components are based on the ME average kilograms produced as opposed to the EBV scores for these traits in order to quantify the net yield fluctuations over time

C. OBJECTIVE 2: HEDONIC PRICE MODEL

In contrast to composite indicators like the LPI, the hedonic price model consists of implied direct monetary values conferred to each attribute of a good or service traded in a market, in our case, semen doses, based on an economic relationship held between the item and its parts (i.e. a semen dose being a unit composed of its genetic potential in different areas). Consequently, the estimation of this model results in marginal effects that are, in turn, interpreted as the direct dollar value implicitly awarded to each attribute from the market transaction for the final, *bundled* product (i.e. the semen dose). Firstly, cross-section Tobit estimations of the hedonic price model homologous to Richards and Jeffrey's (1996) use of 1995 semen transaction and bull proof data will be performed for each year in our data series, between 2008 to 2016, as a means to compare their findings more directly, but also to pick up any nuances in trait variations between the years that followed the increased use of genomics in sire selection. The marginal effects from these annual, cross-section results of the hedonic price modelling are discussed in the following section. Secondly, a model using the aggregate, panel series data (all observations over 2008 to 2016) will be used to address unobserved individual heterogeneity that is specific to cross section estimation (Greene, 2012, 5th ed.). The results from the estimation of the hedonic price model using the entire panel data is discussed in the second section below.

Although our dataset is not a complete panel, since the total number of bull semen sold over time varies, securing a dataset with two dimensions, the individual dimension (i.e. sire specimens) and the time dimension, will help us to assess any existing bias in the year by year regressions arising from omitted variables (Greene, 2012,5th ed.). In addition, different iterations of the regression are assessed in an effort to address collinearity issues among variables and redundancy or over-representation of a trait in the model. Lastly, we take the data away from a Tobit estimation and consider Cragg's Double-hurdle model as an alternative formulation of the dairy market's semen valuation process. Empirical methods thus move away from the standard approach in the literature so far as we seek for the model that best represents the data. The most relevant results from these alternative estimations and their interpretation within the Canadian industry context are reported in this section.

While our research follows a similar method to Richards and Jeffrey (1996), it is not merely providing an update to prior findings. Rather, it sets out to identify possible fluctuations in sire attribute valuation over time to characterize farmers' trait preference structure by testing different iterations and econometric specifications (Tobit, Double-hurdle). The findings on this econometric analysis can aid breeders and policymakers to adjust their selection efforts, economic incentives and regulations towards the enhancement of traits perceived most valuable for producer operations.

1. Hedonic Modelling Results for Year By Year Regressions

This section addresses the marginal effect results from the cross-section tobit regressions for each year in the panel series (from 2008 to 2016)[66]. Firstly, an estimation using the key bull traits is used, milk yield; fat and protein content; conformation; mammary system; feet and legs; daughter fertility and somatic cell score (see **Table 4.3**). In addition, an alternative model, one omitting protein content, is also discussed and contrasted to the base model that includes all traits (see **Table 4.4**). Results are presented for two periods per year, one including purchases between January to July, and another including purchases from August to December, in order to maintain the annual results under a calendar year but also provide an opportunity for researchers with a dairy calendar to assess it under that perspective.

Production traits: Milk components

Fat content is statistically significant up to 2013 to varying degrees - with the exception of the period of August to December 2013 - but statistically insignificant from 2014 onwards. Along with d*aughter fertility*, these two traits had the same number of statistically-significant periods, and were second to f*eet and legs* in terms of significant periods across the separate period regressions (no overarching pattern across all marginal effects was observed, but out of the significant terms, the August to December period had a slightly larger magnitude for 3 of the 6 periods, and one having identical values to the January to July period). The marginal effect values were statistically insignificant on the last three periods of the years studied (Aug-Dec 2015 onwards). The alternative model, on the other hand, had three significant periods with negative marginal effects on price (Jan-July of 2014 and Aug-Dec of 2015 and 2016). Overall, the alternative model observed four more periods where *fat* had statistically significant effects, and together with *milk*, had the greatest amount of significant coefficients among the traits. The alternative model, therefore, suggests to represent farmer valuation more accurately, or approximate it better, since no drastic changes in the other

[66] The direct Tobit regression coefficients for these estimations can be viewed in **Appendix 4**.

variables or their significance was incurred. Removing protein from the model while still including the milk variable is therefore, a more appropriate formulation of farmer preferences in bull selection without any loss in efficiency of the estimation.

Milk had a statistically significant negative relationship with semen cost between the August to December period of 2010 and the August to December period of 2014. Further, this was the third trait with the most statistically significant periods among the key attributes evaluated in the model, but the magnitude of its marginal effect was negligible. The magnitude of the marginal effects over time remained mostly unchanged between periods of the same year and extremely negligible altogether. The alternative model showed *milk*'s marginal effect on semen prices were always negative, and had an outstanding gain in the number of periods with statistical significance (15 total compared to 9 in the baseline model). The value of the marginal effects remained unchanged, however.

Protein, with the exception of 2008, was statistically insignificant for all of the time periods considered. Although it was a negative marginal effect, it was also the largest magnitude from the entire series. There was no particular pattern differentiating the January-July from August-December marginal effects.

Milk component observations in context with pricing policies

The statistical significance of the different milk components is also consistent with the pricing policies that favoured fat production while encouraging less protein content, as well as the rising trend in butterfat demand: As a result of 3-4 % annual increases in butter consumption, skim milk continued to face backlogs to such an extent that "some provinces began to experience absolute surpluses of raw milk without sufficient capacity for processing it" (Mussell, 2016, p.3). The highly correlated relationship between these milk components along with the increasing inventory surplus for solids non-fat (SNF) explain why protein failed to be significant, yet milk remained relevant. In addition, it is interesting that these were among the traits with the most statistically significant marginal effects over the different time periods, but not the greatest in terms of impact on semen price. In contrast to the comparison of bull proofs' statistical averages, and the last hedonic study by Richards and Jeffrey (1996), the hedonic modelling of periodical cross-sections suggests that Canadian Holstein farmers do not prefer production traits on top of their list when making semen selections, although they will consistently keep them under consideration for their decision. These results corroborate the initial conclusion gathered from the statistical comparison of bull proofs earlier: Dairy producers have shifted gears on the category of traits that they most value for breeding decisions. Boettcher (2005, p.9) further adds that this trend can ring "particularly true in countries where the introduction of milk quotas has limited the marginal returns from increasing yield."

Durability components

Conformation was only statistically significant up to the January to July period of 2009. Nevertheless, *conformation* was the largest significant marginal effect compared to the other key attributes for the periods of 2008 and the January to July period of 2009. Interestingly, while this trait was removed from the LPI formula since August of 2001 (originally in the durability category of the formula), our year by year modeling suggests that this trait continued to hold a significant effect in semen selection up to 2009 (CDN, 2001). Further, out of the statistically significant coefficients for *conformation*, the marginal effect of August to December of 2008 had the largest effect. These observations remained true in the alternative estimation, with *conformation* experiencing only slightly greater marginal effects, but comparable, from the standard model coefficients.

This finding is in direct contradiction to the expected dominance of production traits over type traits as observed by Richards and Jeffrey (1996) in their one-year hedonic price modelling in Canada, and Beavers and Van Doormaal's (2015) analysis on trait progression among herds in the country for 5-year time periods. However, it further corroborates similar studies of farmer trait preferences on dairy producers in Australia (Martin-Collado et al., 2015) and West Africa (Tano et al., 2003) and general observations of dairy producers using body condition scores as a proxy for "selection against metabolic disorders and fertility traits" (Boettcher, 2005, p.12). Lastly, it supports Miglior et al.'s (2017) assertion of the dairy industry as turning into a more holistic approach when looking for ideal sire mates to bring about new cow replacements.

A possible reason behind the loss in statistical significance can be due to confounding effects from other *type* traits being highly correlated with *conformation*, as are *mammary system* and *feet and legs*, which in itself explains their lack of significance at the beginning of the periods at hand. Additionally, Boettcher (2005, p.9) suggests that these latter traits could be increasing in importance individually as "the general public is continually becoming more concerned about their source of food" and "healthy animals are likely to produce more healthful food."

Although statistically significant for most of the periods until 2012, *mammary system* ceased to be statistically significant after December of 2012; only one period, January to July 2016 was statistically significant in the remaining years. The greatest marginal effects were observed in August to December of 2010 and 2012. Overall, the coefficients of *mammary system* had larger marginal effects in the August to December period than the January to July periods. The alternative iteration followed the same trend as the baseline model, with almost identical coefficients for the marginal effects, although it did lose one significant period (August to December of 2009[67]).

Again, the high degree of correlation between *mammary system*, *conformation* and *feet and legs* could be behind this, as the regression results show that once *conformation* ceases to be statistically significant, *mammary system* becomes significant and a similar situation happens between *feet and legs* and *mammary system* (although these two had a year of overlapping significant marginal effects). In addition, Boettcher (2005, p.12) notes that traits associated with udder condition also share a genetic correlation with mastitis incidence and thus, have also been used as an indirect indicator of the disease, although their association is "lower than between mastitis and *SCS*.[68]"

Interestingly, *Feet and Legs* did not show statistically significant results until the year of 2011, yet it remained significant until the last period of 2016 afterwards. This trait holds the most statistically significant periods from all the other key attributes assessed in the model. In addition, it maintained a marginal effect coefficient of 0.4 since 2012's August-December period all throughout (except for Jan-Jul 2013). However, most of the coefficients with statistical significance were larger in the August to December periods, although the degree of significance was higher in the January to July periods. The alternative iteration of the model, on the other hand, also showed significant effects starting 2011, and did share with the baseline model the fact that most of its marginal effects approximated a 0.4 per additional unit on *Feet and Legs* scores. Overall, the magnitudes of the marginal effects and the tendency for them to be slightly greater in the August to December periods remained unchanged. Nevertheless, in the alternative iteration model, *Feet and Legs* took the second spot in the number of statistically significant periods, as *EBV Milk* and *Fat* both had 15 against its 12 periods.

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[67] The magnitudes of the year 2008 were larger for the alternative iteration in comparison to the baseline model, but statistically insignificant.

[68] Boettcher (2005) also notes, however, that the heritability estimate between udder traits and mastitis incidence is greater than that of SCS and mastitis.

Similar observations were obtained from the comparison of average scores for the main sire traits among the entire annual bull registry and the top 100-LPI ranking sires, where Feet and Legs was among the top two traits for most positive gains over the 5-year period of 2000 to 2005 and the comparison against the last available publication, 2005 to 2008. Ultimately, these results build on the preference structure of farmers changing towards a pattern that favors health and longevity over production traits when choosing the best sire source. The increased interest in *feet and legs* is also outlined by Boettcher (2005, p.12) as an indirect selection trait against locomotive illnesses and lameness that can, in fact, "yield higher selection accuracy than direct selection against lameness," further supporting this premise of farmers' underlying interests.

Health and Fertility components

*Daughter fertilit*y had statistically significant values between the start of 2009 and 2014 (January to July). It was the second trait, along with *EBV Fat*, in terms of having statistically significant values over time. In addition, it was the trait with the highest amount of highly significant values; nine of the marginal effects had a significant value at the 1% level, and two of them with 5% significance.

Although this trait does not come across as highly correlated to *conformation* in our data analysis, the literature does recognize that producers have used body condition scores "as a criterion for indirect selection against metabolic disorders and to help improve the reliability of genetic evaluation for reproductive traits" even though the degree of heritability towards those traits is low (Boettcher, 2005, p.12). Tano et al.'s study (2003) of West African cattle producers also found that 'reproductive performance' ranked among the most valued traits for farmers, while Australian farmers at large identified fertility as one of the top three traits most interested to improve on[69]. Interestingly, the marginal effects in our year-by-year estimations showed that, as *daughter fertility* became statistically significant, *conformation* ceased, which could provide further evidence that preference towards direct selection of the trait instead of a proxy with low heritability success became more pronounced in 2009.

[69] Their decision-making focused first on the fertility of the semen itself as well as the "EBV of the bull for production and management traits", and then, on a second plane, considered "type and herd test data of the daughters of the bull" (Martin-Collado et al., 2015, p.4155).

Alternatively, the heavy investment on cow genomics by the top five Canadian AI firms could also have played a role in the loss of significance after 2014 (Hunt, 2014; Greig, 2018). Since 2012, companies like Alta Genetics, ABS Global, Genex' co-op program, EDG- Sexing Technologies, De-Su and S-S-I held the top index animals and owned over 50 percent of the best 100 females (Hunt, 2014). Similarly, Semex, the largest genetic dairy company in Canada, is now one of the ten organizations that hold up to 80 percent of the best female genetics worldwide (Greig, 2018). This shift in dynamics starting from 2012 could also have a role in the loss of perceived value of daughter fertility in farmers' sire selections. The degree to which this supplier structure could overtake the voluntariness aspect of genomic adoption into breeding decisions by farmers is beyond the scope of this study, but should be considered when analyzing the results of our estimations.

On the other hand, *Somatic Cell Score* was only statistically significant for three years, from August-December 2012 to January July of 2015, but its marginal effects on semen cost were by far the largest from all the attributes. Half of the statistically significant coefficients across all regressions had higher values on the August to December periods. The alternative iteration, which removed *protein*, lost one significant marginal effect (January-July 2015), but the magnitudes of these had similar values to the standard model, and still remained the most substantial effects from all the other traits over all the different years. Further, the marginal effects of *SCS* from August to December of 2013 stood out as the greatest among the different coefficients for this trait and the remaining trait values. The large impact that *SCS* had on semen price is corresponding with the high costs and profit losses associated to mastitis treatment as highlighted by Hailu et al. (2015), their survey results showing Ontario producers having a moderate to high concern over mastitis, and Australian type-farmers favoring improvements on mastitis, longevity and fertility the most (Martin-Collado et al., 2015). In addition, it correlates with Boettcher's (2005, p.8) insight on the changing management priorities of farmers as their operation size increased but the total farm numbers decreased:

> "In today's large farms, the owner may act primarily as a supervisor and financial manager. In this role, the farmer may be more aware of the costs of production than in the past. The functional traits generally have their impacts on the costs of production, rather than on income. [...] The effects on profit of a particular health problem, mastitis for example, may be more obvious than for a small farm without computerized health records."

Table 4.3 Marginal Effects for Tobit estimation of Hedonic Semen Cost model; annual estimates (cross section data for 2008-2016)

	2008		2009		2010		2011	
	JAN-JUL	AUG-DEC	JAN-JUL	AUG-DEC	JAN-JUL	AUG-DEC	JAN-JUL	AUG-DEC
EBV Milk	0.003	0.001	-0.002	-0.001	-0.001	-0.002*	-0.002*	-0.003**
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
EBV Fat	0.093**	0.144***	0.069**	0.048*	0.032*	0.028	0.038*	0.067***
	(0.035)	(0.031)	(0.020)	(0.020)	(0.017)	(0.018)	(0.018)	(0.019)
EBV Protein	-0.198*	-0.157*	-0.007	0.002	0.022	0.037	0.013	0.020
	(0.083)	(0.067)	(0.040)	(0.038)	(0.031)	(0.035)	(0.033)	(0.034)
Conformation	0.845*	1.085**	0.573*	0.256	0.190	0.047	-0.151	-0.143
	(0.407)	(0.329)	(0.229)	(0.213)	(0.182)	(0.196)	(0.190)	(0.209)
Mammary System	-0.104	-0.089**	0.255	0.388*	0.318*	0.534**	0.44**	0.397*
	(0.350)	(0.288)	(0.200)	(0.192)	(0.161)	(0.173)	(0.166)	(0.187)
Feet & Legs	0.040	-0.040	-0.144	-0.088	0.022	0.080	0.249*	0.330**
	(0.220)	(0.181)	(0.133)	(0.128)	(0.106)	(0.112)	(0.104)	(0.110)
Daughter Fertility	-0.187	-0.116	-0.434***	-0.451***	-0.411***	-0.370***	-0.359***	-0.476***
	(0.173)	(0.159)	(0.103)	(0.101)	(0.086)	(0.092)	(0.089)	(0.095)
Somatic Cell Score	-2.381	0.546	1.558	-1.708	-0.058	-0.380	1.277	1.778
	(3.671)	(3.192)	(2.071)	(2.054)	(1.747)	(1.923)	(1.881)	(1.990)
Likelihood Ratio	-488.405	-680.771	-2101.183	-2365.005	-3194.726	-3264.931	-3496.655	-3582.525
Predicted Y	$ 25.82	$ 24.67	$ 22.87	$ 22.95	$ 22.06	$ 24.23	$ 24.14	$ 25.60

	2012		2013		2014		2015		2016	
	JAN-JUL	AUG-DEC	JAN-JUL	AUG-DEC	JAN-JUL	AUG-DEC	JAN-JUL	AUG-DEC	JAN-JUL	AUG-DEC
EBV Milk	-0.002*	-0.003**	-0.003**	-0.003**	-0.003**	-0.003*	-0.001	-0.001	-0.001	0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
EBV Fat	0.052**	0.053**	0.037*	0.037*	0.029	0.026	0.002	-0.021	-0.008	-0.016
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.020)	(0.019)	(0.020)	(0.020)	(0.026)
EBV Protein	0.010	0.016	0.022	0.012	0.011	-0.005	-0.028	-0.039	-0.040	-0.076
	(0.033)	(0.034)	(0.034)	(0.034)	(0.035)	(0.037)	(0.036)	(0.038)	(0.037)	(0.052)
Conformation	-0.161	-0.327	-0.128	0.001	0.169	0.268	0.039	0.135	0.297	0.353
	(0.207)	(0.216)	(0.216)	(0.217)	(0.215)	(0.235)	(0.227)	(0.239)	(0.234)	(0.314)
Mammary System	0.3101*	0.452*	0.066	-0.031	-0.217	-0.268	0.020	-0.128	-0.379*	-0.442
	(0.183)	(0.190)	(0.188)	(0.191)	(0.191)	(0.208)	(0.200)	(0.214)	(0.214)	(0.293)
Feet & Legs	0.342**	0.384**	0.449***	0.4**	0.44***	0.437**	0.346**	0.417**	0.404**	0.435*
	(0.110)	(0.112)	(0.114)	(0.116)	(0.118)	(0.129)	(0.125)	(0.133)	(0.127)	(0.172)
Daughter Fertility	-0.412***	-0.499***	-0.373***	-0.278**	-0.229**	-0.105	-0.116	-0.050	-0.030	-0.071
	(0.091)	(0.090)	(0.087)	(0.088)	(0.086)	(0.089)	(0.084)	(0.085)	(0.082)	(0.109)
Somatic Cell Score	1.974	4.527*	4.353*	6.181**	5.677**	4.63*	3.62*	1.566	0.147	1.724
	(2.006)	(1.987)	(2.018)	(2.053)	(2.064)	(2.189)	(2.058)	(2.124)	(2.100)	(2.880)
Likelihood Ratio	-3967.409	-4032.430	-4741.497	-4836.269	-5096.476	-5032.996	-5280.752	-5379.231	-5628.122	-4382.999
Predicted Y	$ 26.30	$ 26.71	$ 28.19	$ 28.54	$ 29.24	$ 30.75	$ 29.82	$ 31.11	$ 30.65	$ 35.60

*=α significant at 10%, **= α significant at 5%, ***= α significant at 99% | Standard deviations provided in parentheses
For Tobit regression coefficients, see **Appendix 4**.

Table 4.4 No Protein, Hedonic Semen Cost model; Marginal Effects for annual Tobit estimation (cross-section data for 2008-2016)

	2008		2009		2010		2011	
	JAN-JUL	AUG-DEC	JAN-JUL	AUG-DEC	JAN-JUL	AUG-DEC	JAN-JUL	AUG-DEC
EBV Milk	-0.002	-0.002*	-0.002**	-0.001*	-0.001	-0.001*	-0.001*	-0.002**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
EBV Fat	0.053*	0.111***	0.068***	0.048**	0.037*	0.037*	0.041**	0.073***
	(0.031)	(0.027)	(0.018)	(0.018)	(0.015)	(0.017)	(0.016)	(0.017)
EBV Protein								
Conformation	1.098**	1.210***	0.580*	0.254	0.174	0.022	-0.159	-0.151
	(0.405)	(0.329)	(0.226)	(0.209)	(0.181)	(0.195)	(0.189)	(0.209)
Mammary System	-0.329	-0.233	0.248	0.39*	0.334*	0.558**	0.446**	0.402*
	(0.347)	(0.286)	(0.197)	(0.188)	(0.160)	(0.172)	(0.166)	(0.186)
Feet & Legs	-0.032	-0.055	-0.146	-0.088	0.028	0.086	0.252*	0.332**
	(0.220)	(0.183)	(0.133)	(0.127)	(0.105)	(0.112)	(0.104)	(0.110)
Daughter Fertility	-0.158	-0.085	-0.434***	-0.451***	-0.414***	-0.367***	-0.355***	-0.468***
	(0.176)	(0.160)	(0.103)	(0.101)	(0.086)	(0.092)	(0.089)	(0.094)
Somatic Cell Score	-3.708	-0.519	1.537	-1.701	-0.164	-0.027	1.396	1.927
	(3.725)	(3.200)	(2.068)	(2.049)	(1.718)	(1.894)	(1.857)	(1.975)
Likelihood Ratio	-491.283	-683.519	-2101.200	-2365.006	-3194.976	-3265.488	-3496.73	-3582.708
Predicted Y	$ 26.40	$ 24.99	$ 22.87	$ 22.95	$ 22.07	$ 24.24	$ 24.14	$ 25.60

	2012		2013		2014		2015		2016	
	JAN-JUL	AUG-DEC	JAN-JUL	AUG-DEC	JAN-JUL	AUG-DEC	JAN-JUL	AUG-DEC	JAN-JUL	AUG-DEC
EBV Milk	-0.002**	-0.002***	-0.002***	-0.002***	-0.003***	-0.003***	-0.002**	-0.001*	-0.002**	0.0003
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
EBV Fat	0.055**	0.058***	0.043**	0.042**	-0.032*	-0.025	-0.005	-0.031*	-0.019	-0.038*
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.018)	(0.017)	(0.017)	(0.017)	(0.022)
EBV Protein										
Conformation	-0.166	-0.339	-0.145	-0.006	0.165	0.270	-0.047	0.135	0.290	0.339
	(0.206)	(0.215)	(0.214)	(0.217)	(0.215)	(0.234)	(0.227)	(0.239)	(0.234)	(0.315)
Mammary System	0.314*	0.462*	0.080	-0.024	-0.212	-0.270	0.013	-0.125	-0.372*	-0.425
	(0.182)	(0.189)	(0.187)	(0.190)	(0.190)	(0.208)	(0.200)	(0.214)	(0.214)	(0.293)
Feet & Legs	0.344**	0.387**	0.456***	0.404***	0.442***	0.436**	0.34**	0.411**	0.403**	0.432*
	(0.110)	(0.111)	(0.113)	(0.115)	(0.118)	(0.129)	(0.125)	(0.133)	(0.127)	(0.172)
Daughter Fertility	-0.408***	-0.494***	-0.367***	-0.273**	-0.223**	-0.107	-0.127	-0.066	-0.044	-0.094
	(0.090)	(0.089)	(0.087)	(0.087)	(0.084)	(0.087)	(0.083)	(0.084)	(0.081)	(0.108)
Somatic Cell Score	2.045	4.646*	4.555*	6.288**	5.76**	4.604*	3.532	1.573	0.214	1.997
	(1.993)	(1.971)	(1.994)	(2.029)	(2.047)	(2.180)	(2.056)	(2.125)	(2.100)	(2.877)
Likelihood Ratio	-3467.459	-4032.543	-4741.707	-4836.329	-5096.524	-5033.005	-5281.044	-5379.76	-5628.703	-4384.084
Predicted Y	$ 26.30	$ 26.71	$ 28.20	$ 28.54	$ 29.24	$ 30.76	$ 29.84	$ 31.13	$ 30.67	$ 35.64

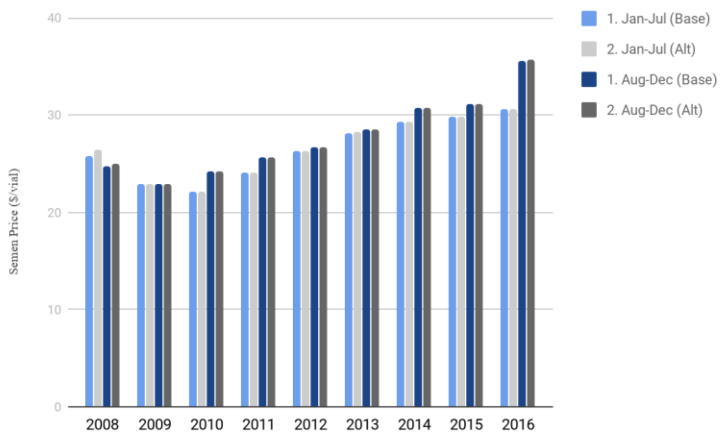
*=α significant at 10%, **= α significant at 5%, ***= α significant at 99% **|** Statistically significant values are bold **|** Standard deviations provided in parentheses
For Tobit regression coefficients, see **Appendix 4**.

Predicted Semen Cost Values

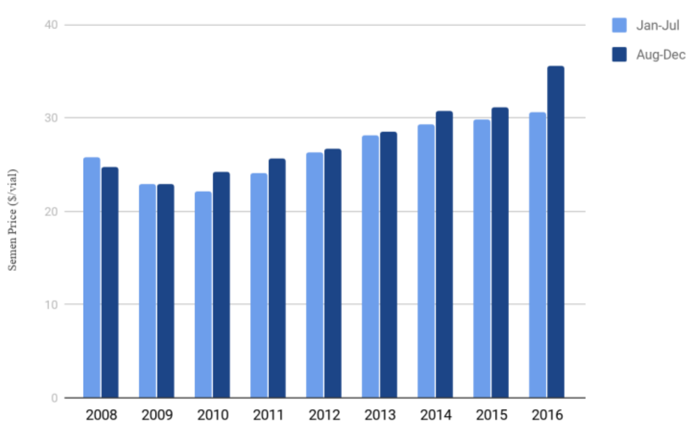
The price predicted for an average semen sample ranged from $22.06 in January to July of 2010 to $35.60 in August to December of 2016. All of these predicted prices fell within the standard, actual price range, where the low-end fell at the $24 -per straw value and the high-end samples were reported to hit $50 or even $100 (Jokinen, 2016). Overall, the general fluctuation over time for the predicted semen prices followed an increasing trend in average semen prices from August-December of 2010 forward, however. The predicted semen prices under the alternative model, where EBV Protein was removed from the considered explanatory variables, also shared the same trajectory and trend.

Figure 4.1 Fluctuation of predicted Semen price over time, baseline (1) vs. alternative (2)

i. Predicted Semen prices over time, (1). vs. (2)



ii. Predicted Semen prices for Baseline model (1)



2. Analyzing the Average Marginal Effects of Key Bull Attributes on Semen Prices During 2008 to 2016

Hedonic modeling for the panel data over the entire time period of 2008 to 2016 further underlines the overarching theme of producer preferences favoring health and longevity traits as outlined through our first objective results. The hedonic price modelling of semen prices using the overall panel series assessed several attribute combinations under a Tobit specification as well as a Cragg Double-Hurdle specification. Firstly, a baseline estimation including all of the key bull attributes (*milk* yield, *fat* and *protein* content, *conformation*, *mammary system*, *feet and legs*, *daughter fertility* and *somatic cell score*) was assessed. The results of this baseline regression are discussed in this section. Additional iterations analyzing the effect of the different milk components on semen price as well as the impact of highly correlated variables on each other (conformation, mammary system and herd life) is also discussed in the following two sections.

The most interesting observation for the key bull attributes is that *somatic cell score (SCS*) has the greatest impact on semen prices, where a rise in 1 unit of this index would lead to a rise of $2.18 in the price of a semen dose. This is consistent with Hailu et al.'s (2016) finding regarding Ontario farmers' concern for mastitis incidence; where 53% of respondents were highly concerned and 43% had some or little concern. Further, considering that Hailu et al.'s (2016) results suggested that farmers' value-adding focus was driving their response towards adopting mastitis-genotyping technology, the marginal effects of *SCS* in our hedonic modeling could be signaling farmers' priority to cut down costs of this prevalent disease when constrained by quota limitations and milk pricing schemes. The ranking of *SCS* in the panel estimation results reflects the year-by-year more nuanced findings. Once again, this outcome goes against the inferences obtained when merely looking at the statistical description of bull proofs over time in our first objective, yet it aligns with the results from the year-by-year hedonic modelling. Moreover, our econometric analysis resonates with Martin- Collado et al.'s (2015) qualitative research on Australian dairy farmers; their survey results also showed that producers were most concerned with improvements on traits related to mastitis, longevity and fertility. The importance of this divergence in conclusions lies in the fact that it underlines the crucial value that this econometric exercise plays as a tool for uncovering farmer valuation of sire traits.

The second and third largest marginal effects on semen price were *conformation* and *feet and legs*, respectively, although neither of them surpassed a 0.5 magnitude. These observations continue to indicate that farmers are especially concerned with securing the rate of return of their semen investment by improving the resilience of their future cows, and thus cut down on treatment bills and replacement costs, as pointed out by Boettcher (2005). Again, this inference is directly opposite to Richards and Jeffrey's (1996) last analysis, which found *feet and legs* had no "significant independent influence on the perceived marketability of a bull when "final class" is already included." Although *feet and legs* was heavily correlated with traits like *conformation* and *mammary system* in our series, both the year-by-year regressions and the panel data regressions demonstrated that this trait was consistently significant on semen prices regardless. Instead, the results support Miglior et al.'s (2017) assertion of the industry trend towards a more health and longevity-focused mindset, and Tano et al.'s (2003) study of West African cattle farmers, where disease resistance profiled as one of the most valuable traits for producers.

The marginal effects of the remaining attributes on semen prices also remained under the 0.5 value. A surprising observation was that the effect of *milk* and *daughter fertility* (DF) on semen prices were negative (milk was significant at 10%, DF significant at 1%). Lastly, it was interesting to find that the greatest impact on semen values among the three milk components was EBV *fat*, followed by EBV *milk* and lastly, EBV *protein* (given its lack of statistical significance). The ordering of the milk components is in agreement with the Canadian milk payment strategy, which, having implemented a butterfat differential in 1993, moved to a butterfat content minimum and a shift in pricing of $3 per kilogram for butterfat more but $3 per kilogram less for protein in 2004, and finally, the establishment of a national fluid-milk pricing formula in 2010 still favoring butterfat content (Kennelly et al., 2017). Nevertheless, their weak statistical significance and meager effect on semen price when compared to the marginal effects of *SCS*, *conformation* and *mammary system*, for instance, signal that the economic returns from the milk components are not the main determinant in producers' semen purchasing decisions. Further, the staggering rise in skim milk powder (or solids non-fat, SNF) production stocks from 55, 400 tonnes in 2004-2005 (CDC, 2006) to 70, 000 tonnes in 2014 despite these pricing incentives (Kennelly et al., 2017), would also explain the reason behind protein's lack of statistical significance in the price of semen. Similar findings from West African dairy farmers by Tano et al. (2003) also showed that milk yield and weight gain were significant traits for cattle but to a lesser extent than resilience to disease and fertility, while Martin-Collado et al (2015) found Holstein farmers to be type-focused, a group that was particularly highlighted to be interested the least in protein yield. Finally, the high level of correlation between *protein* and the *fat* (0.805) and *milk* (0.888) in the dataset and the "very strong genetic correlations" between these traits (Miglior et al., 2017, p.10253) also play a role in observing protein's effect on semen prices as insignificant.

In addition, the effects of *mammary system* and *protein* were not statistically significant on semen prices. Similar to Richards and Jeffrey's (1996) observation of existing synergies among type attributes like *feet and legs*, *mammary system* and body *capacity* in their hedonic price estimation, the lack of significant marginal effects of *mammary system* on an individual basis supports the case for the close correlation between them and other traits included in the regression (e.g. *conformatio*n, and *feet and legs* with *mammary system* as well), being at play and creating confounding effects.

Table 4.5 Marginal effects from Tobit estimation for baseline regression (a)

	Coefficient	Std. Dev.
EBV Milk	**-0.0096***	0.0005
EBV Fat	**0.022***	0.009
EBV Protein	0.011	0.017
Conformation	**0.451*****	0.107
Mammary System	-0.001	0.095
Feet & Legs	**0.378*****	0.059
Daughter Fertility	**-0.163*****	0.041
Somatic Cell Score	**2.180***	1.007
Predicted Y ($/sample)	28.14	

*=α significant at 10%, **= α significant at 5%, ***= α significant at 99% **|** Statistically significant values are bold **|** Standard deviations provided in parentheses
For Tobit regression coefficients, see **Appendix 4**.

Overall, this baseline regression would support that type attributes are chief in the priority ranking of producers when selecting an ideal semen sample, opposite to Richards and Jeffrey's (1996) observation two decades ago. Furthermore, the levels of significance on these attributes also highlight *conformation* and *feet and legs* as highly significant, while the effects from EBV *milk, fat* and *SCS* were only significant at the 5 percent confidence level. Nevertheless, *somatic cell score* showed the highest impact on semen prices, almost a hundred-fold larger than the effect nearly five times that of *conformation* and slightly over 57 times greater than the effect of *feet and legs* despite it only having a 5 percent level of significance.

2.1 Milk components: Comparing results and significance levels f or attributes among iterations

In order to assess the possible correlation effect on the level of significance of each milk component and their corresponding impact on semen prices, several iterations with a single of these traits, as well as one regression that only removed *EBV milk* - in accordance to the LPI formula - and one removing *EBV protein*, were calculated.

The marginal effects for *EBV fat* remained significant in all iterations where it was included, maintaining its level of significance at 10 percent. Nevertheless, an outstanding finding was that the marginal effect of fat on semen prices fell by 40 percent when only the *fat* component was considered and no other bull attribute seemed to pick it up. A similar observation was found for *EBV protein*, which failed to have a significant effect on semen prices across all the different iterations. Once *EBV protein* was removed, however, we observed that *EBV milk* was significant, and more importantly, EBV fat gained another degree of significance from the baseline model (a). No loss in the degree of significance or drastic changes in the marginal effects of the remaining traits was observed. Lastly, when removing *protein* and *fat* from the regression (iteration g), the *milk* component alone continued to be statistically insignificant. Additionally, *EBV milk's* magnitude did not absorb the value of the other milk components, but was instead 98.76 percent smaller. However, in this last regression, the magnitudes of the different bull traits were comparable to the baseline iteration, although the *SCS* effect was indeed diminished by 26 percent and ceased being statistically significant. Once more, our results support the assertion that milk component pricing was not the sole driver of farmers' purchasing decisions for Holstein semen.

Another interesting change on the remaining attributes was that of *mammary system* once the milk component was removed (iteration d); its marginal effect on semen prices, albeit still statistically insignificant, became positive and the absolute value of the coefficient dropped to a third of its original effect under the baseline conditions (regression a). Evidently, the correlation among these traits is a crucial source of bias that can only be considered when assessing results but not completely eradicated, since these relations hold biologically as well. Parallel to the cross-section regressions, the different combinations of milk component variables confirm that *protein* fails to be significant under any iteration, but suppressing it provides a more statistically significant marginal effect of *fat* without any additional cost on overall efficiency of the regression's other estimators.

Table 4.6 Marginal effects from Tobit iterations without a milk component against the baseline regression (a)

	a. Baseline	b. No Fat	c. No Protein	d. No Milk	e. Only Fat	f. Only Protein	g. Only Milk
EBV Milk	**-0.01*** (0.0005)	**-0.001*** (0.0005)	**-0.001*** (0.0003)	----	----	----	-0.0001 (0.00024)
EBV Fat	**0.022*** (0.009)	---	**0.025**** (0.008)	**0.023**** (0.009)	**0.014*** (0.0006)	---	---
EBV Protein	0.011 (0.017)	**0.033*** (0.015)	---	-0.015 (0.011)	---	0.005 (0.008)	---
Conformation	**0.451***** (0.107)	**0.473***** (0.107)	**0.447***** (0.107)	**0.438***** (0.011)	**0.439***** (0.107)	**0.461***** (0.107)	**0.472***** (0.107)
Mammary System	-0.001 (0.095)	-0.013 (0.095)	0.002 (0.095)	0.0004 (0.095)	-0.008 (0.095)	-0.012 (0.095)	-0.007 (0.095)
Feet & Legs	**0.378***** (0.059)	**0.387***** (0.059)	**0.381***** (0.059)	**0.391***** (0.059)	**0.392***** (0.059)	**0.402***** (0.059)	**0.404***** (0.059)
Daughter Fertility	**-0.163***** (0.041)	**-0.162***** (0.041)	**-0.159***** (0.040)	**-0.148***** (0.040)	**-0.15***** (0.040)	**-0.146***** (0.040)	**-0.145***** (0.040)
Somatic Cell Score	**2.180*** (1.007)	**1.73*** (0.990)	**2.21*** (1.006)	**2.16*** (1.007)	**2.036*** (1.004)	**1.679*** (0.99)	1.609 (0.988)
Predicted Y ($/sample)	28.14	28.15	28.14	28.14	28.15	28.15	28.16

*=α significant at 10%, **= α significant at 5%, ***= α significant at 99% | Statistically significant values are bold | Standard deviations provided in parentheses
For Tobit regression coefficients, see **Appendix 4**.

2.2 Conformation and Mammary System

The high degree of correlation observed between the *conformation* and *mammary system* attributes also called for analyzing the semen price regression without both of these components together. As mentioned earlier in this chapter, the initial results where all the key variables were included showed that *conformation* was highly significant and the second most valued attribute for Canadian farmers when making their semen selection. *Mammary system*, on the other hand, had the smallest impact among all of the traits; although it showed a negative effect on semen prices, it was not statistically significant. As acknowledged in the data analysis and the methodology of this study, the nearly-perfect collinearity with conformation (correlation factor is 0.92) generated the reduced degree of impact that mammary system effected on semen price when both were included into the model.

Once *conformation* was removed, however (iteration h), *mammary system*'s effect on semen prices became positive and strongly significant. Moreover, its marginal effect increased dramatically (in absolute terms); the coefficient was 252 times greater than the baseline value and took third place in the ordering of attribute preference for semen selection.

The marginal effects for *feet and legs*, *daughter fertility*, and *somatic cell score* also increased from the original, baseline values by 39 percent, 25 percent (in absolute terms) and 14 percent, respectively (their degree of significance remained the same). The results show that the high degree of collinearity among *conformation* and *mammary system*, *feet and legs* and *daughter fertility* that was observed in the data analysis in Chapter 3 is interfering with the valuation of these correlated traits. While our approach of excluding the most troubling variable, *conformation*, did bring about a change in the value of *feet and legs*, *daughter fertility* and *mammary system* (which was insignificant otherwise), the marginal effect of *milk* on semen prices became 92 times smaller from its original, baseline effect (0.0008 as opposed to 0.01 in the baseline regression that included *conformation*, see Table 4.7).

Alternatively, when *mammary system* was removed from the regression, (iteration i) the marginal effect of *conformation* and degree of significance remained unchanged from the original baseline values (0.451 vs. 0.449). The same was observed with the rest of the bull attributes; the marginal effects reverted back to the baseline coefficients. The marginal effect of EBV *protein* continued to be statistically insignificant on semen prices.

Table 4.7 Marginal effects from Tobit estimations without Conformation (h) or Mammary System (i) against the baseline results (a)

	a. Baseline	h. No Conformation	i. No Mamm. System
EBV Milk	**-0.01*** (0.0005)	**-0.0008*** (0.0005)	**-0.001*** (0.0005)
EBV Fat	**0.022*** (0.009)	**0.026**** (0.009)	**0.022*** (0.009)
EBV Protein	0.011 (0.017)	0.008 (0.017)	0.011 (0.017)
Conformation	**0.451***** (0.107)	----	**0.449***** (0.052)
Mammary System	-0.001 (0.095)	**0.347***** (0.046)	----
Feet & Legs	**0.378***** (0.059)	**0.526***** (0.048)	**0.378***** (0.056)
Daughter Fertility	**-0.163***** (0.041)	**-0.203***** (0.04)	**-0.163***** (0.04)
Somatic Cell Score	**2.180*** (1.007)	**2.482*** (1.006)	**2.183*** (1.000)

*=α significant at 10%, **= α significant at 5%, ***= α significant at 99% **|** Statistically significant values are bold **|** Standard deviations provided in parentheses
For Tobit regression coefficients, see **Appendix 4**.

2.3 Herd Life

Although previous analysis by Richards and Jeffrey (1996) concluded that composite measures like Final class (a phased-out measurement) were too closely associated to related bull attributes, this present study did not reveal highly statistically-correlated relationships among *Herd Life* and other variables used as indicators for longevity, like *Feet and Legs* and *Mammary System*, so separate iterations were also included to assess the alternative scenario of including herd life into the key attributes considered during semen selection.

The inclusion of *Herd Life* (HL) into the regression changed the magnitude and the direction of certain other attributes in regards to their marginal effect on semen prices. The most drastic change was that of *SCS*, which became statistically insignificant and 18 percent of the original baseline value (in absolute terms) and negative. Similarly, the effect of *mammary system* on semen prices became positive, instead of negative, and despite remaining statistically insignificant, the absolute value of this coefficient increased 92-fold from the original baseline value, while *daughter fertility* (DF) also became insignificant and its magnitude was reduced by 92 percent. *Conformation* lost one level of statistical significance and 18 percent of the marginal effect it exerted on semen prices. Therefore, under this iteration, *feet and legs* ranked first in priority, followed by conformation and then herd life.

Table 4.8 Marginal effects from Tobit estimations including Herd Life (j) against baseline results (a)

	a. Baseline	j. Herd Life included
EBV Milk	**-0.01*** (0.0005)	**-0.001*** (0.0005)
EBV Fat	**0.022*** (0.009)	**0.022**** (0.009)
EBV Protein	0.011 (0.017)	0.019 (0.017)
Conformation	**0.451***** (0.107)	**0.368**** (0.109)
Mammary System	-0.001 (0.095)	0.128 (0.099)
Feet & Legs	**0.378***** (0.059)	**0.433***** (0.061)
Daughter Fertility	**-0.163***** (0.041)	-0.013 (0.005)
Somatic Cell Score	**2.180*** (1.007)	-0.402 (1.141)
Herd Life	-----	**-0.325***** (0.061)

*=α significant at 10%, **= α significant at 5%, ***= α significant at 99% | Statistically significant values are bold | Standard deviations provided in parentheses
For Tobit regression coefficients, see **Appendix 4**.

3. Cragg Double Hurdle Results

In response to the distribution of the semen price data, a Cragg Double-Hurdle model, also called a two-step regression, was also considered as a functional form for our hedonic price estimation. As the frequency distribution revealed (see Chapter 3), the series did not fully comply with the censored normal distribution assumed by the Tobit model, and thus, an additional method that would relax this expectation was also contemplated. This last estimation suggested that in the first phase of the decision, the selection hurdle (i.e.

the decision to participate in purchasing Holstein semen), the most significant trait was *somatic cell score*, then followed by *conformation*, then *daughter fertility* and *feet and legs*. While the milk components of *fat* content and *milk* yield were still significant in this step, their effect was very small in comparison to the other traits, as was observed in the marginal effects from the tobit estimations. However, as the second hurdle was estimated, the marginal effects for this purchasing decision (i.e. how much to purchase given that they decided to participate in the semen market) only had *conformation* and *feet and legs* as strongly significant, with fat content just significant at the 5% level.

Table 4.9 Cragg Double-Hurdle estimation of Hedonic price model, Panel series 2008-2016

	Selection	Semen Price	Marginal Fx	Std. Dev.
Constant	**1.368**** (0.503)	**-40.698**** (15.525)	----	----
EBV Milk	**-0.0001**** (0.00004)	**0.003*** (0.001)	-0.0007	(0.0007)
EBV Fat	**0.002**** (0.0008)	0.002 (0.026)	**0.027***	(0.012)
EBV Protein	0.002 (0.002)	-0.05 (0.047)	0.012	(0.024)
Conformation	**0.038***** (0.009)	**0.542*** (0.315)	**0.627*****	(0.153)
Mammary System	-0.010 (0.008)	**0.836**** (0.272)	0.163	(0.134)
Feet & Legs	**0.021***** (0.005)	**1.067***** (0.17)	**0.612*****	(0.084)
Daughter Fertility	**-0.028***** (0.003)	**0.721***** (0.112)	-0.085	(0.057)
Somatic Cell Score	**0.345***** (0.089)	**-10.643***** (2.823)	0.460	(1.414)

*=α significant at 10%, **= α significant at 5%, ***= α significant at 99% | Statistically significant values are bold | Standard deviations provided in parentheses

D. OBJECTIVE 3: COMPARING THE WEIGHTED RANKING OF BULL ATTRIBUTES IN THE LPI FORMULA TO THE VALUATION REVEALED FROM HEDONIC PRICE MODELING

In this last section of our discussion, we reconcile the observations from the historical data and the results from the econometric analysis with the priority ordering of the traits displayed in the LPI formula. Our last objective is to evaluate if this indicator accurately reflects the preference pattern sought by Canadian producers when making sire selection choices. This objective ties together the empirical aspect of our study with the direct, industry and policy implications derived from our results, as the values conferred in the market to each trait from a semen dose transaction, via a hedonic price estimation, can provide a blueprint of trait categories to emphasize in selection programs and how to arrange weighting schemes or monetary incentives around these.

In broad terms, the health and fertility indicators composed the least amount of priority in the LPI formulation, changing from the original 15 percent to 20 percent of the total score from 2015 onwards. Similarly, the 2005 weights in the formula set up daughter fertility on a level of importance nearly sevenfold to that of *SCS*, but the econometric results failed to support this relationship among the traits, and instead suggested the opposite. Instead, the results of these hedonic price modeling exercises would further align with Martin-Collado et al.'s (2015) findings on Australian dairy farmers, whose cluster analysis showed Holstein farmers tended to be type-focused in their bull selection- making, while Jersey farmers were more production-focused. This farmer typology was characterized by preferring improvements for mastitis, longevity and mammary system traits, as well as looking for superior fertility and temperament scores but regarding protein yield as the least important trait (Martin-Collado et al., 2015). The observations of our study closely support Australian dairy producers' preference structure.

As explained in the previous section, the marginal effects of attributes like *somatic cell score* and *daughter fertility* on the semen price had the highest level of impact among the different explanatory traits of the model, while *protein* remained statistically insignificant across all iteration alternatives and its magnitude was never above the effect of the rest of the traits (*protein* was only significant in the iteration where *fat* was removed). Lastly, the effect of *SCS* on selection decisions was designated as negative in the LPI formula, but the econometric analysis only agreed with this set up of the LPI when herd life was included into the regression (iteration *m*). Under these conditions, *SCS* ceased to have a statistically significant effect on semen prices, however. Although the updated LPI formula of 2015 selected more heavily on *conformation*, *fat* and *protein* (Beavers and Van Doormaal, 2015), the emphasis on *SCS* is not present in this selection indicator.

The results of the Hedonic pricing models, although aligning with Holstein Canada's latest statements on farmer behaviours, as well as other choice experiments performed under different dairy market conditions (i.e. Australia is not under a supply-managed dairy system), would not be represented in the weight structure of Canada's main indicator, the Lifetime Profit Index, LPI. Additional findings from Martin-Collado et al.'s (2015) choice experiment was that type-focused farmers, as Holstein producers were categorized, tended to have less confidence in the accuracy of the relative weighing of traits and their own profit-ranking indicator, the APR (Australian Profit-Ranking Index). The parallel of our findings to their results would suggest that Canadian Holstein farmers also find a discrepancy between their priority structure and the LPI scoring system. Further, while the Canadian Dairy Network recognized that the LPI does not directly translate to profit gains and it stressed that the index concerned itself with genetic merit (CDN, 2014; Beavers, 2017), the results of this econometric analysis suggest that their emphasis did not focus on the main traits that farmers use to gain genetic improvements in their herds[70].

E. CONCLUSION

This study set out to uncover Canadian dairy producers' trait preference structure when choosing semen doses to purchase in the Holstein sire market. Particularly, this research sought to identify the values assigned to the key traits outlined in the literature and assess if their effect on semen prices changed significantly over time and especially, after the increased use of genomics in the Canadian sire selection industry in 2008.
These objectives were pursued by using annual sire proof publications from Holstein Canada to calculate and compare average score fluctuations over time prior to the increased use of genomics in the country, as well as by estimating a series of Hedonic Price regressions, year by year and as a panel data series. Finally, our analysis also aimed to compare our valuation results from the econometric estimations to the weighting assigned to the key sire attributes in the main selection indicator in Canada, the LPI, and assess if the formula's priorities were representative of farmers' preference structure.

[70] The LPI weights set production components (milk and fat) at 51 percent and durability at 34 percent (herd life, mammary system, feet and legs and conformation), with health and fertility at 15 percent (includes somatic cell score and daughter fertility) in 2008 and changed them in August of 2015 to 40, 40 and 20 percent, respectively (Beavers and Van Doormaal, 2015).

The comparison between the mean scores of the average bull and the top-ranking bull from the proof records of 1995, 2000, 2005 and 2008 coincided with Richards and Jeffrey's (1996) picture of Canadian dairy producers; a heavy production-focused mindset driving sire selections up to the late 90s. Average scores showed that milk component values were higher for the top 100 LPI-ranking bulls, with milk and fat being the most favoured of the components since 2005. On the other hand, the average EBV scores for both samples, total registered bulls vs top 100 bulls, decreased in value over time, yet the total kilogram volume of all milk components showed a contrasting, upwards trajectory; as the national data attests to, the average milk volume yields were increasing across the country's herds over time. Ultimately, however, it is the large discrepancy between the mean sire and the top-ranking sire's on *feet and leg* scores that stands out as a key indication of the developing change in trait preferences to more type-related attributes, as reported by Miglior et al. (2017) and in line with Martin-Collado et al. (2015). The comparison in mean values reinforced the fact that durability components like *feet and legs*, *dairy character* and *mammary system*, were much more significant to farmers than production traits, and thus underrepresented by the LPI weights.

The superior scores of the top-ranked sires attest to Rogers' theory of innovation (2003, 5th ed.), which suggested that a subset of the population will take risks and be able to invest in new technology or methods before uptake snowballs to the rest of the producers. Further, the relevance of this comparative analysis lies in the gap observed between the mean scores of the top-ranked bulls and the total sire registry, especially in the milk components and *Feet and legs*. The variations across time for the different bull samples (the total registered pool and the top 100 LPI- ranking bulls), while still upholding milk components came first, hinted towards *type* attribute prioritization second.

The Tobit regressions of each cross-section highlighted the importance of *type* traits for producers' selection decision of Holstein semen more clearly. Overall, the year to year Hedonic price estimations also observed a pronounced interest in health-related traits, particularly *conformation, feet and legs*, and s*omatic cell score*. The sustained statistical significance of the milk components throughout the majority of the period regressions is consistent with the degree of importance that the dairy industry set to milk components above all traits, as we can appreciate from the pricing policy and the LPI-weighting system, but these never surpassed the effect of the health-related traits mentioned previously. The alternative iteration removing protein from the explanatory variables continued to demonstrate this health-durability focused pattern; no substantial changes in other variables' magnitudes was observed but additional marginal coefficients gained significance for the remaining milk components across the different time periods. Ultimately, the contrasting value of the milk traits in terms of the magnitude of their marginal effect on semen price against the industry's high regard for them shows that producers effectively shifted gears away from production traits being the chief element in their breeding decisions.

On the other hand, confounding effects due to correlation between many of the variables seem to be behind the lack of significance in other related traits like *mammary system* and *daughter fertility*. This factor, together with many of these traits' low heritability could be the reason for a lack of more evident changes in their average scores, which, in turn, hinders the accuracy of direct year-to-year statistical analysis as a means to uncover farmers' preference structure. Additionally, other circumstances such as poor quality of the data collection system in place (Miglior et al., 2005; Boettcher, 2005), and the changing cow landscape with AI servicing companies investing in cow genetics and displacing breeders (Greig, 2018; Hunt, 2014) could also be affecting the results we observed.

The additional estimations of the hedonic price modeling using the panel data series further corroborated these findings. The different iterations removing milk components confirmed that including both, *EBV protein* and *EBV milk*, into the regression did not provide the most efficient characterization of farmers' decision process, but it did suggest maintaining *EBV milk* along with *EBV fat* would render the most appropriate formulation that encompassed the butterfat and the solid-non-fats components that constitute milk sales in Canada. Similarly, *mammary system* became highly significant once *conformation* was removed from the regression's explanatory variables. More importantly, its marginal effect on semen prices became positive instead of negative, as observed under the baseline conditions (regression *a*). The marginal effects of this and other related traits, such as *feet and legs*, *daughter fertility*, and *somatic cell score* also increased from the original, baseline effects on semen price, which further strengthened the case for confounding effects from correlated variables. Lastly, running an estimation with *Herd Life* included showed that, while lacking statistical correlation with other traits, its inclusion greatly affected the statistical significance and value of other attributes whose influence is well-grounded by other studies and industry experience. As a result, the greatest takeaway from these alternative iteration analysis we gather is that care must be taken when interpreting the results of any formulaic calculation regarding dairy attributes, as their close relationship, biologically and economically, is a major source of bias to determine the true impact of each attribute.

Overall, the hedonic price analysis consistently showed health-related and body-condition type traits as the most valued by farmers during their sire selection purchases. Further, while milk components had the strongest statistical significance among the traits, they also had the smallest marginal effect on semen's market prices. The findings of the hedonic price modeling in this study mirror the major takeaways from Martin-Collado et al.'s (2015) analysis of Australian dairy farmers, which found Holstein producers to be mostly *type*-focused during their sire selection. The implications of this analogous results would suggest that the applicability of Martin-Collado et al.'s (2015) findings would also extend to Canadian Holstein farmers.

Nevertheless, caution should be made on the extent of which our results characterize each Holstein farmer in Canada. Rather, as it was emphasized in the methodology of this chapter, a hedonic price model will only yield an average picture of breeding selection decisions over the population. Richards and Jeffrey's study (1996) also raised the concern in regards to the data used for the calculations of the LPI, as it relied too heavily on average operation costs from Ontario at the time of their analysis, and questioned the applicability of their budget scenario to other provincial contexts. This present study did not take provincial heterogeneity into consideration, so the extent to which the particularities of each Province are still represented in these results is worth studying further to reach a general hedonic price model that accurately describes Canadian farmer preferences for bull attributes during semen selections.

As it pertains to the third objective, the results from the Tobit and Double-Hurdle models showed that there could be a discrepancy in the market valuation of traits and the values assigned to traits in the LPI formula. The marginal effects from these hedonic price estimations show different priority rankings for the individual traits than those that are present in the LPI formula through the weights assigned to each attribute, which suggests that farmers using the LPI as a main source of reference might become dissatisfied with the outcomes they achieve. Similarly, Martin-Collado et al. (2015) also found a section of their respondent pool found "that the APR[71] does not weight traits according to their needs," which further underscores the disconnect between the indicator formulas and producers' preference structures as a generalized pattern in the industry. The results fail to support the assertion that the LPI formula can represent the economic value of

[71] APR: Australian Profit Ranking. The Australian analog of Canada's LPI.

each trait to producers as shown in semen transactions along with the bull's inherent potential to generate economic profit.

While the LPI continued to place a higher focus on the production front of sire traits, our marginal effect results strongly supported the conclusions made about the dairy industry favouring improvements in health and durability traits in their breeding decisions over production traits. This divergence may have led the way for other indices, like PRO$ to be created and align more closely to farmers' interests. Ultimately, our observations only draw conclusions from the average, aggregated preference structures of Canadian farmers, and care should be taken to apply these findings to all individual producers. As it was highlighted by Martin-Collado et al. (2015) and Howley et al. (2012), producers are not homogeneous in their preferences (nor cattle's performance throughout their lifespan), such that a single index (or estimation method) may only work for a subset of farmers (and life stages of cows/sires).

This research provides evidence in favor of relying on econometric methods to identify producers' preference structure in the future, as well as overhauling the weight system and genomic efforts and policies geared towards the durability and health components of cows. Ultimately, we recognize the limitations of our study in regards to the nature of the data series, the high degree of correlation between traits and the limits of the econometric model itself should be kept in mind when assessing the validity of our results. Our research provides a bridging block in the literature gap left after the last analysis of the Canadian dairy industry by Richards and Jeffrey (1996) and finds external validity with similar findings from studies performed across the world. However, future studies employing different methodologies or expanding on the variables employed or the nature of the data can further aid in painting an accurate picture of dairy farmers' sire selection behaviour. Further research extensions and the application of these current findings are discussed in the following and final chapter.

Chapter 5 . CONCLUSION AND FUTURE EXTENSIONS

A. REVIEW OF FINDINGS AND MAIN OBJECTIVES

This study set out to identify dairy producers' valuation of key sire attributes for the selection of breeding bull semen over time. Moreover, one purpose of this analysis was to assess if there has been a discernible change in producer preferences after the introduction of genomics to the Canadian sire semen market. Using actual market data of Holstein semen purchases as a way of measuring the value of the key bull attributes, this study looked to identify the relative ranking of these traits in producers' semen-purchasing decisions over time, especially after the increased use of genomics in sire selection started in 2008. Ultimately, the results revealed which sire traits are most important to Canadian farmers for breeding preferences. This information can be integral to the development and fine-tuning of genetic improvement plans and the weighing of these attributes in the main sire selection indexes.

Since the selection of a sire determines the genetic potential for the entire operation's herd, and thus, the operation's production and financial potential, this study focused on farmers' decision-making behaviour during the semen selection process. Moreover, this analysis used semen transactions of Holstein sires, the most used breed in the Canadian market, to uncover producers' attitudes towards bull-attribute priorities in breeding. More than just providing an update for the last study on farmer's valuation of Holstein sire attributes in Canada by Richards and Jeffrey (1996), the ultimate objective of this study was to uncover if the industry's conclusions drawn from production and price statistics and rates of change in sire traits over time are consistent with what the econometric analysis reveals about farmer preferences with newer data. For this purpose, the research focused on periods before and after the inclusion of new genomic information in breeding, 2008, through a Hedonic Price Model. Considering the nature of the database available for the analysis, a large unbalanced panel series (48 percent of the observations suffered from lower-bottom censoring at $0), this study was able to perform MLE regression methods for the entire panel as well as individual estimations for cross sectional subsamples (observations were separated by years based on the active status of the semen sample). Finally, the econometric methodology relaxed the restriction of the Tobit I specification on the variables' effects by also considering a Cragg Double Hurdle model in the study.

Relevance and implications of study

Producers are faced with the economic problem of optimizing the profitability of their operation while still satisfying public demands in order to succeed in the market. In the Canadian dairy context, the main challenge for producers is to minimize cost under supply management production limitations. Further changes in the milk pricing formula and increases in the imported dairy product volumes due to the implementation of trade deals like the Canada-US-Mexico (CUSMA), the CETA and the CPTPP could curtail milk revenues for farmers, limit future quota increases and ultimately, place a greater pressure on producers to reduce their milk production costs even more (Farm Credit Canada (FCC), 2020). Under this environment, the use of genomics to design a more efficient and long-lasting herd will be crucial in delivering profits to Canadian dairy operations. Genomic innovations in breeding have the potential to surmount the ceilings that producers currently encounter in their production if they are willing to adopt this technology during their sire selection and ultimately, change their herd composition.

The accurate determination of farmers' priorities during their sire selection decisions is thus vital to linking producers to other key players in the dairy industry as well as to their end consumers. Further, as farmers' concerns change and market realities change, it is critical to update assessments of producers' breeding objectives using newer annual data. Ongoing evaluation of farmer preference patterns for sire attributes will ensure that the scientific principles used to generate the weights in selection indexes are consistent with farmers' attitudes as revealed through economic transactions in the market.

B. REVIEW OF METHODOLOGY RATIONALE AND NATURE OF THE DATA

The bulk of this study centered on the econometric analysis of semen price data using sire attribute scores as explanatory variables. Prior to this step, however, historical data was collected from Holstein Canada's annual bull proof publications to close the gap between the last econometric analysis of the Canadian Holstein semen market in 1995 (Richards and Jeffrey, 1996) and the period where the increased use of genomics in sire selection programs began to influence the market in 2008. Sire data was collected for the years of 1995, 2000, 2005 and 2008 and used to compare average score values across this time period as well as to contrast these scores against a subset of the entire sire population (composed of the top 100 LPI-ranking sire scores alone). Additionally, this analysis was also valuable to contrast the findings from the direct evaluation of statistical data over time to the traits' implicit values obtained from the econometric regression analysis. While securing transaction information associated with the registered sires for this period was not accessible for this study (bull proof publications do not include semen prices nor availability status of the semen), compiling the trait scores for the registered sire pool of these years contributed to the study by building a profile for bull performance in this interim time period as well as to provide a base to compare the econometric assessment's predictive power.

This research introduced new attributes into the explanatory variables considered for the hedonic modeling and evaluated their valuation over time across a larger sample size, using both, cross-section and panel series to provide a comparison to Richards and Jeffrey's (1996) study and expand on it further. The long time horizon available in the dataset also allowed for individual, annual, cross-section estimations to be run and compared against the general panel set across the entire period, which revealed the changing preference trends for each attribute over time. In terms of the methodology applied in this study, the econometric applications included relaxing the basic Tobit restriction on the parameters and allowing the data to identify the most appropriate effects by expanding the analysis to include a Cragg double-hurdle model. While the Tobit specification accounted for the Type I censoring of the semen prices in our database (any price under $5 was recorded as zero and 49% of the transactions in our data series had zero as a sale price), it still subjected the data to an assumption of a normal censored distribution. A closer inspection of the semen price distribution (see **Fig 3.1** in Chapter 3) suggested that the heavy long tail might not be consistent with the Tobit assumption, requiring us to also consider a Cragg double-hurdle model. The Cragg Double-Hurdle model accommodates a different distribution by separating the estimation of the semen purchasing decision into a selection step (i.e. the first hurdle, where a producer decides on whether or not to participate in the market (to buy semen or not at all)) and the *decision-spending* step, where the producer decides how much spending to incur on for the particular semen dose (i.e. the hedonic model setting defined previously as semen price being a function of the bull traits) (Duan et al.,1983). The use of different functional forms in this study gives way to building a more precise interpretation of dairy farmers' attitudes in the sire selection process. Consequently, the preference results can also be used to compare to the weighting of the attributes in the main selection index for Canada, the LPI. In the case where observable differences are identified, these can then contribute to the development of breeding programs catered towards the improvement of the key attributes that Canadian farmers desire and, to develop support systems that accelerate or encourage industry objectives.

Inadequacies of this modeling include the limitations associated with the dataset, like the unbalanced nature of the panel series, as bull numbers dwindled and specific specimens changed over the years, for instance, as well as the censored semen prices below the threshold of $5 for 51.25 percent of the database, posed substantial challenges to obtaining robust inferences from the results. Nevertheless, the predicted semen prices for the different cross-section estimations and the aggregated, panel estimation coincided with real-market average prices for semen sales in Canada (Jokinen, 2016). The estimations showed the trend supporting health and durability-related traits in semen purchases are at the forefront of producers' minds (Boettcher, 2005; Miglior et al., 2017; Hailu et al., 2017). Further analysis using a more comprehensive database that can capture the variability and depth in the decision-making process with fewer sources of bias, such as securing uncensored semen prices, a database with balanced bull numbers across years and maintaining the same bull specimens throughout the study period, could help corroborate the findings in this present study.

Other missing information that could be considered in future studies as additional variables would be the sourcing of the bulls (by embryo transfer or other); temperament; mastitis resistance; genotyping data available, polled or unpolled; genomic sire or proven, for instance. The addition of these attributes into the regression analysis would add significantly to the characterization of farmers' preference for attributes during their breeding considerations. Furthermore, it would enable a better understanding of the different attributes to select for through genomic technologies for breeders and AI companies to focus on, as well as provide an action plan for policymakers in regards to extension services or incentive programs to instate when encouraging the uptake of specific sires over others. Notwithstanding, the results gathered from these estimations have shed light on the prioritization of sire traits as well as the breeding decision-making pattern for the average dairy farmer, after the introduction of genomics in the sire selection toolset.

C. SUMMARY OF RESULTS AND IMPLICATIONS

This study set out to test the value of key sire traits individually as a share of their monetary contribution to semen prices in the Canadian market, to estimate their variation over time after the increased use of genomics in selection programs and to compare the results with the weights established in the LPI index. A measurement of the fluctuation in average trait scores prior to the increased use of genomics was pursued pre-emptively to dispel any assumptions regarding gains in trait areas or the value of econometric estimation compared to direct statistical analysis as the first objective. Consequently, the second objective sought to perform hedonic price function estimations to further build the case for this method's applicability in the dairy market as a straightforward means to elicit the individual values of key bull proof characteristics and to track observable changes in their valuation over time.

Hedonic pricing helps to identify the monetary value associated with each trait by farmers based on real-market semen transactions and further allows the cross-comparison of similar studies performed across the globe to dairy producers in the Canadian setting. Our results demonstrate that the need to find alternative routes away from value-adding or expanding operations has potentially exacerbated producers' type-trait preference behaviour to ensure reduced costs of production or maintenance of their herds (treatment costs and heifer replacement, for instance). Ultimately, managing to identify producers' trait preference structure correctly is a crucial step in future revisions of national selection indicators like the LPI to be able to accomplish breeding objectives in genomic programs that align with producers' operation goals and the industry requirements.

1. OBJECTIVE 1

The first objective dealt with closing the gap between the last study on dairy farmer selection behaviour in 1995 (Richards and Jeffrey, 1996) and painting a picture of trait progress prior to the uptake of genomic technology in breeding of 2008. The historical proof data used in this objective ranged from 1995 to 2008; it picked up from the last study on breeding selection choices in Canada (Richards and Jeffrey, 1996) up to the year where the use of genomics increased in the country, 2008. An assessment of the fluctuation in average scores for the most relevant sire traits was performed over the complete sire registry and for a subset of bulls, the top 100 LPI-ranking sires. The widest difference observed between these samples within the same year was observed in the milk components, where the top-ranking bulls outperformed the general bull population. This finding reflects Richards and Jeffrey's (1996) concluding emphasis on production traits (milk yield, protein and fat content), as well as the priority given to them in both, the Canadian milk payment scheme and the LPI formula weights. In addition, the overall superior scores by the top-ranked bulls resonate with the advantage found in the most productive herds studied by Beavers and Van Doormaal (2015). The overall superior performance of the top-ranked bulls observed in the trait score comparison against the overall bull population also aligns with Rogers' theory of innovation model (2003, 5th ed.), which explains that the most risk-taking, and informed producers will continuously invest more into the latest innovation in production until it reaches popular adoption by the vast majority.

Nevertheless, the most remarkable observation from our results was the outstanding importance that type-related traits (e.g. mammary system, feet and legs, conformation) held in relation to the commonly favored production traits. After the milk components, the largest discrepancies within the same year were for scores associated with traits in the durability category, namely *Feet and legs*, *dairy character*, *conformation*, *mammary system*, and finally, *capacity*. However, the score difference between top-ranking LPI bulls and the general bull population across time shows a bigger decline in durability and health and fertility-related traits than the differences between those same populations for milk component traits. While milk component differences grew over time (milk gap grew to 57.7 percent in 2008 from 38 percent in 2000, fat gap rose to 78 percent in 2008 from 42.7 percent in 2000 and protein difference also grew to 66.7 percent in 2008 from 44.5 percent in 2000), scores like *conformation* score, originally 60.4 percent more for top-ranking bulls in 2000 was only 21.4 percent greater than the general bull population average by 2008, while *feet and legs*' gap was only 40.4 percent in 2008 from 73 percent in 2000, for instance. Somatic cell score, however, had imperceptible differences between the top-scoring bulls' and the general bulls' average. Overall, changes over time in terms of these differences between both samples diminished for the durability and the health and fertility traits, which suggests that producers continually selected for certain functional traits, even at the cost of gains in production. A more pronounced pattern along this line was observed when the comparisons over the years were calculated.

In both of these sire groups, the top-three traits in terms of score fluctuation were related to the durability category of the LPI formula. Average scores for EBV milk, fat and protein, on the other hand experienced large drops, although the net yields in terms of average kilograms produced (ME[72] 2 year average kg) continued growing. Ultimately, the price adjustments in the regulated milk components did not suffice to explain the large fall in EBV scores for milk components, but rather, it suggested that Canadian sires' genetic potential for yield capacity could be homogenizing as lower-producing specimens were removed from the market and the number of farms diminished. Our modelling results offer breeders, policymakers and dairy boards further insights on farmers' interest for durability and health traits and identify a potential contrast with the weights of the LPI formula, which continues to allocate a heavier weight to production traits (see Chapter 2, **Table 2.1**). Ultimately, this study's observations suggest the need for a readjustment of breeding improvement goals towards these farmer-desired traits.

2. OBJECTIVE 2

The second objective of this thesis sought to estimate the value of key sire traits to Canadian farmers through an econometric approach and analyze if there had been any perceivable changes in their valuation over time effect after the increased use of genomics in 2008. A hedonic price model was selected as a way to obtain the implicit value of each individual bull trait by regressing semen prices as a function of these key sire traits for transactions between 2008 and 2016. This objective analyzes the potential effect on trait valuation by the new high-density genotyping chip, the Illumina Bovine SNP50 in 2008 (Taylor et al., 2016). While different factors, such as the ease of identifying and measuring trait performance, the increased use of young genomic bulls and producers' better understanding of genomics, may all contribute to the changes in the values ascribed to the key sire traits by dairy farmers, the scope of research centered solely on revealed preference data (semen sale prices and bull trait

[72] Mature Equivalent units: Milk, fat and protein yield measurements for cows converted from BCA values (Breed Class Average units). MEs are calculated as [Cows yield in kg/ avg yield for age and month] x [avg yield for mature cow], (Robinson et al., 1994).

scores). The semen purchase data is first analyzed by estimating year by year Tobit regressions of the hedonic price model and then an overall estimation of the entire panel data from 2008 to 2016. The marginal effects consistently showed *somatic cell score* as the most significant trait in semen prices, then followed by *conformation*, and *feet and legs*, then *daughter fertility*.

The average valuation by an average Canadian dairy producer revealed by the hedonic price modelling in our study corroborated prior findings on Australian Holstein growers, which noted this group of producers were type-trait focused, valuing improvements in mastitis resistance, longevity and mammary system the most, as well as caring for type, fertility and temperament for bull selection (Martin-Collado et al., 2015). Similar findings were reported from developing countries in West Africa, where cattle farmers also ranked disease resistance, fertility and a measure of fitness as the most important attributes, with weight gain and milk yield on a lesser rank than the others (Tano et al., 2003). This would suggest that dairy producers respond in similar manners to optimize their herds regardless of the capital available or market structure they face. While Richards and Jeffrey (1996) highlighted the different milk productivity components as the most valued attributes, followed by *conformation*, *capacity* and a measure of repeatability (number of daughters), our results showed that the average marginal effect of these attributes was more attuned to Boettcher and Van Doormaal's (1999) latter observations, which concluded that longevity and health were being more carefully considered in sire selection decisions. Additionally, the lack of statistical significance of milk protein on semen prices also corresponded with Martin-Collado et al.'s (2015) observations of Holstein farmers in Australia; type-focused farmers cared for protein the least of all the typologies identified in their study.

The findings of this study fail to support the inclusion of protein into a regression analysis of semen selection behaviour, but it did find the *milk* and *fat* statistically significant to semen prices (See Chapter 4, **Table 4.3**, **4.4**, **4.6** and **4.9**). These results further suggest that removing *protein* from the LPI index and replacing it with the overall *milk* component instead would increase the indicator's representation of farmers' priorities. Similarly, the iterations evaluating closely-related traits like *conformation* and *mammary system* also showed a marked increase in the values of *mammary system*, *feet and legs*, *daughter fertility* and *somatic cell score* once *conformation* was removed from the explanatory variables (see Chapter 4, **Table 4.7**). These results and the nearly-perfect collinearity between *mammary system* and *conformation* and the highly collinear relationship between *feet and legs* and *conformation* (0.92 and 0.752, respectively, see Chapter 3, **Table 3.3**) strongly support removing *conformation* from any econometric modeling and indicator calculations to avoid biased estimations of the key sire trait values on semen price. Future extensions on this study could analyze a model that excludes *protein* and *conformation* simultaneously and compare the results against these findings.

Lastly, the high marginal effect of *somatic cell score* on semen price found throughout all the different iterations of the hedonic modeling brought forward a key concern for producers that was otherwise unprecedented in previous statistical analysis of average trait average and gains tracking alone. Since dairy production is fixed through the quota system, results suggest that Canadian farmers are focusing on increasing revenue by preventing treatment expenses or replacement costs from sickly cows, as ascertained by Hailu et al. (2017), and also avoiding associated penalties of surpassing the somatic cell count content[73].This finding is of pivotal importance for the formulation of the LPI, as the current version does not reflect the importance of health traits in its weighting. Our results further build the case for relying on econometric price estimations to analyze any observable changes in producer preference structure for key sire traits and to rely on their forecasting power for building breeding program objectives, policy packages and extension programs. Most importantly, these observations provide an implicit suggestion on producer attitudes towards genomics: The high valuation of these lowly-heritable traits like *somatic cell score*, *feet and legs* and *daughter fertility* (Miglior et al., 2017; Garcia-Ruiz et al., 2016) above the rest of the key sire attributes in semen selection indicates that producers are willing to accept the use of genomic tools to improve their herds beyond the limits of traditional breeding methods.

Nevertheless, consideration should be given to the limitations of the econometric modeling performed and the nature of the datasets when evaluating the validity of our interpretations. As previously stressed, hedonic price models are theoretically composed from a collection of meeting points from individual offer curves and bid curves, yielding results that reflect the average population

[73] In 2012, farmers face penalty rates of $3, $4 and $5 per hectolitre for their first, second, third or additional infractions within a rolling 12-month period if the standard for somatic cell count was surpassed (limit set at 5000,000 cells per millilitre in 2007) (Mann, 2012). The potential ban from the milk market can also happen if a farmer incurs in four somatic cell count penalties in any rolling 12-month period (Mann, 2012).

bid and offer for a good; it will not leave room for niche groups or different typologies to be described in the results. As Martin-Collado et al. (2015, p.4157) mention, “in situations where farmers’ preferences for trait improvements are likely to be heterogeneous [...] mean values of farmers’ preferences may give an incomplete and biased view of the farmers’ preferences.” Similarly, Hagerman et al. (2017, p.1) noted, “livestock valuation method selection was not one-size fits all and may need to vary based not only on the data available but also on the characteristics (e.g. quality or age) of the livestock being valued).” Ultimately, we acknowledge the possibility of different methods being more suited to pick up on the producer typologies of the nation or the livestock types. While this study used actual price data (semen transactions in the Canadian market) to reflect the value of different traits, stated preference methods are also possible tools to establish farmer interest in particular traits. Different approaches to address this obstacle in our methodology are proposed in our next section.

3. OBJECTIVE 3

The marginal effects across the different iterations and functional forms of the hedonic modeling in this study showed that the scores calculated through the LPI may not reflect the market value of a particular semen sample from a producer’s valuation stance. If the LPI aims to aid producers decide on a semen source by ranking sires based on the likelihood of profitability (from the future daughters that result from that particular bull selection), this study’s findings show that the current formula may not be entirely consistent with farmers’ preference structures. While the index has evolved to accommodate market conditions (see Chapter 2, **Table 2.1**), it has not matched what producers have identified as their main needs at the same time, potentially a result of lagged reactions. Consequently, this index may not serve AI companies or breeders as a signalling mechanism for which traits to focus their genomic efforts on in their breeding programs. It is also possible that the development of other more recent indices, such as the Pro$ may better reflect producer preferences, although further analysis was not viable at this time without access to the formula of this index.

As it has been acknowledged in the literature, the development of a single index for the entire sector may not pick up individual farmer preference variability, but focusing on one single, aggregate score certainly facilitates a reliable point of reference for farmers and industry players to compare and assess. However, the LPI may need to update its formula weights (in favour of health and fertility and on a second plane, durability-related traits), as well as to include additional traits (dairy character/temperament) to reflect the attributes that are not only, reliable in selection and which are believed to influence cost the most at a particular point in time, but which also satisfy farmers' preference structure. Alternatively, considering the development of individualized optimization strategies that easily allow producers to use their own weights in the development of individualized breeding formulae is another solution that Canadian dairy organizations could add to the toolset of breeding decisions.

The results continue to provide support to past literature asserting that indices like the LPI cannot be used simultaneously to aid producers achieve the highest economic profits and guide geneticists and AI companies on their breeding targets (Richards and Jeffrey, 1996; Martin-Collado et al, 2015). The fact that Australian farmers' were also found to think that their own selection indicator, the APR, did not weight sire traits in agreement with their operational needs (Martin-Collado et al., 2015) further confirms the generalized nature of this phenomenon across the dairy industry worldwide, independent of milk pricing policies (i.e. free market or supply-managed) and highlights the need for indicator formula weights to be individualized.

D. FUTURE RESEARCH AND EXTENSIONS TO THIS STUDY

This section will elaborate further on new additions in the modeling that we found worth studying, as well as touch on other econometric specifications available to solve our trait valuation question. The first section will go through important variables found in the literature that have not been part of the LPI formula but hold promise to be of significant importance in farmers' semen selection decisions. Secondly, several alternatives to the Tobit I model we chose in this analysis as well as the Cragg Double-Hurdle model are assessed. Lastly, we consider including other aspects that could be influencing producers' breeding decisions, such as incorporating the social networking component effect. Ultimately, we recognize that this industry is rapidly changing and farmers' preference structure, in turn, does not remain stagnant either. Consequently, continued updates and expansions of this analysis are necessary to understand the evolution of sire trait valuations and accommodate farmers' needs into the breeding programs and legislation.

1. Addition of other traits and interactions among variables

Inclusion of other equally-important and relevant bull attributes

Based on the assessment of the literature, the recent changes in the formulas of the main dairy performance and profit index in Canada (the LPI), and this study's summary statistical analysis of historical Holstein data, it is this author's strong recommendation that the array of attributes used in the Hedonic Price Model (collected and reported for each bull) be expanded to include components such as temperament, mastitis resistance, polled or unpolled, genomic sire or proven. Temperament, especially, has been found to affect "the probability to become pregnant during a 90 day natural breeding season" in research from University of Florida (Cooke et al., 2009, p.29), as well as lead to higher "health treatment costs and number of days treated" for less docile cows (Selk, 2015, p.7). Further, Boettcher and Van Doormaal (1999, p.9) had noted that, "Canadian producers have expressed a desire for genetic information on milk temperament since it affects their culling decisions, and therefore profitability." These could greatly help derive farmers' attribute valuation and willingness to pay for genomic technology more accurately using econometric methods and even possibly increase the frequency of genomic testing on farmers' dairy herds, and ultimately, improve the entire genomic selection process for the industry.

Age of the bulls in question is another component worth incorporating into the modelling of farmer trait preference, as the Canadian Dairy Network and other industries report a steady rise in the use of younger sires over older proven sires, in addition to the findings by Hagerman et al. (2017) on different econometric methods having different strengths and blind spots depending on the age of the cow and the nature of the data. Since the deployment of genomic technology has brought about an increase in the use of younger bulls in the Holstein semen market, the valuation of age and daughter productivity data (proven sires) would assist in better tailoring sires for Canadian operations. The fact that the uptake of younger semen has continued to grow in the last decade may suggest that farmers prefer genomics testing over waiting for daughter productivity data required for proven sires. The strong marginal effect of somatic cell score, a trait that has very low heritability (Miglior et al., 2017) could suggest that trust in genomic technology is also growing among Canadian Holstein producers, or is to the very least, neutral to positive, as indicated in Hailu et al.'s (2016) survey results. Finally, analyzing the hedonic price modeling results without including *protein* or *conformation* but adding *milk* into the key sire attributes considered, as suggested from our observations in the second objective, would provide a more efficient baseline for eliciting dairy farmers' sire trait preference in Canada.

Interaction terms

Further interactions among the attributes and other elements associated with the semen transaction observations, like the total number of inseminations and the key bull attributes, or the interaction effect of the years in which the semen was in active use on the bull attributes would be worth investigating in future studies. Although the addition of more interaction variables into a regression would incur efficiency costs in terms of degrees of freedom, it could also inform us better in the relationship that these site attributes hold with the most prolific sires. In other words, it could better delineate the preference patterns followed for picking a semen sample more than once.

Are all farmers created equal? While production economic theory has outlined producers' behaviour is driven by the same underlying principle of profit maximization observed in firms (Heady and Jensen, 1954), case studies on a particular population of farmers, like Howley et al.'s (2012) study of Irish dairy producers or Kaaya et al. (2005), for instance, show that the approach towards attaining maximum utility is not identical between them. The rise in niche markets such as organic dairy or producing local can have different effects on the valuation of traits and the willingness to accept genomic innovations. The Canadian Dairy Commission (CDC) (2017b) noted that organic milk production continued to grow and was, by 2017, 33.8 percent of the milk volume of 2012 (mostly from Québec, Ontario, Alberta, and British Columbia).

In our particular study, it is clear that using Hedonic Price Modeling for bull traits identified in the data (collected per bull) can only approximate the average sire-attribute values across the population of Canadian farmers. Nevertheless, not every farmer in the population will weigh the traits the same way nor will they hold the same attitudes towards this particular technology adoption. These nuances can only be captured by methods that use stated preference approaches like contingent valuation (CV) or choice experiments (CE). As Martin-Collado et al. (2015, p.4148) pointed out in their analysis of Australian dairy farmers, “the determination of farmers preferences is not trivial because of its large heterogeneity.” Ouma et al. (2007) and Kaaya et al. (2005) have also opted for this approach in East African communities when determining producer preferences for cattle traits. Finally, Hagerman et al.’s (2017) study on Irish livestock sales suggested that the type of data available and livestock evaluated, like a young high quality heifer versus a 10-year old cow, would call for a different technique each, where Vector Error Modelling (VECM) did best for national heifer calf sales data and younger cows. Considering the use of VECM while continuing to use aggregated transaction data might also be appropriate for the younger bull semen that is increasing in the Canadian market.

2. Experimenting with other model specifications

This study found a wealth of avenues available to approach our economic problem of farmer trait valuation during semen selection. Given the nature of the dataset, our choice of methodology was the most immediate and direct of the options. This section provides suggestions to address the question of farmer trait preference using the same type of data but different functional forms or adding another factor, the social network effect, into the considerations as Hailu et al. (2017) considered in their study on willingness to pay for mastitis resistance genotyping. While additional, stated preference methods are also available, our expansion of this study will mostly focus on suggestions that can be applied to similar revealed preference datasets as the one this analysis used.

2.1 Sample selection model applications to deal with potential bias in unbalanced panel

Under the assumptions of this study, the missing observations of semen transactions through time in the series were considered an exogenous process. Nevertheless, the reasons behind the unbalanced nature of the panel series could actually be due to endogenous situations, like the more successful sires being constantly selected for, while eliminating the others, or only selecting younger bulls. The former situation would introduce a selection bias to the results and require more robust methods to account for this possible confounding variable issue in the estimation.

In this case, other data collection methods that control against the potential attrition bias like applying a sample selection model that relaxes the assumption of ‘no selection bias’ in the unbalanced panel, such as a Heckman, or a Roy specification, would be the next extension of this analysis when confirming the consistency of this study's results. Comparative studies of this nature have been done in other food consumption areas such as consumer demands for shrimp (Wan and Hu, 2012) and in medicine (Duan et al., 1983), but are not commonly present in this industry or other agricultural studies related to farmer behaviour.

2.2 Random versus Fixed Effects Tobit specifications

Taking these facts into consideration and differentiating the groups within the overall dairy farming population would thus be another promising study. In a continued effort to further understand the Canadian farmer rationale for breeding decisions, adding clusters or breaking down the data into typologies following Howley et al. (2012) in Ireland's study is another possibility that has not been repeated in the Canadian market. Similarly, comparing against the beef producers' decision-making process as well as studying the valuation of beef bull attributes and selection of beef sires over dairy sires in dairy operations is also a note-worthy avenue with the evolving developments in the dairy market.

Recent reviews by the Canadian Dairy Network (CDN) (2019), shows that Holstein cows are increasingly being bred to beef sires since 2002, reaching 5 percent in 2016 and doubling to 10 percent by 2018 (CDN, 2019). Producers are choosing to mate their poorest-performing cows to beef-sires to be able to sell the heifers for a premium sale price instead of producing more dairy heifer replacements and rearing them until they are sold off (CDN, 2019). This new strategy needs to be accompanied with similar breeding management mechanisms as dairy heifer replacement, but with carcass traits like "ribeye, carcass weight and frame size, rather than marbling" taking priority (Slater, 2020). This developing activity has not been studied in Canadian literature with econometric methodology, but given the CDN's observations (2019), it could become increasingly relevant in the next coming years. Finally, potentially making use of milk production end consumers or the provincial milk board that the different dairy farmers supply would be the next suggested focus.

3. Social networking and risk attitudes

On the other hand, when considering stated preference approaches, adding another dimension to the analysis from a social networking perspective could also increase our understanding of farmer's decision-making process when selecting a sire for the stocking of their dairy herd, as explored in Hailu et al.'s (2016) studies. As their study on a sample of Ontario dairy farmers showed, the interaction effect of risk attitudes and social interactions was highly significant in the stated willingness to pay for the genotyping of their cows for mastitis resistance (Hailu et al., 2016). Their contingent valuation analysis also revealed that behavioural factors like belief in genomics and concerns about mastitis exerted an influence in producers' willingness to genotype their herds (Hailu et al., 2017). Similarly, the effect from "extension services", in this case online-access to an entire sire catalog from the newly-formed partnership between Valacta and the Canadian Dairy Network, *Lactanet*, is a new component in the Canadian dairy landscape that could provide producers with increased access to information but also, easier selection mechanisms. The degree to which this new information channel can affect producers' perceived usefulness for the key traits and the use of genomics is valuable to the understanding of the Canadian dairy landscape when making breeding decisions yet to be expanded on.

E. CONCLUDING REMARKS

Our results show that Canadian farmers are favoring type attributes over production traits, with health-related traits like somatic cell score (SCS) and feet and legs taking increasing priority in their breeding selection decisions. As the econometric estimations for Canadian semen purchases confirmed, producers "currently place a higher value on improved functional traits than on increased production" (Boettcher, 2005, p.9). Potentially a result of consumers' interest in animal health and the automation of many daily chores in the barn, dairy farmers have taken on a larger supervising role and emphasized cutting costs of production as their management strategy. Ultimately, these choices reinforce producers' profit-maximizing goals and underscore their interest to attain economic efficiency as explained by Heady and Jensen (1954). The implications for the dairy sector that can be derived from our observations relate to characterizing farmers' preference structure and leading the way forward in genomic selection efforts for sire improvements.

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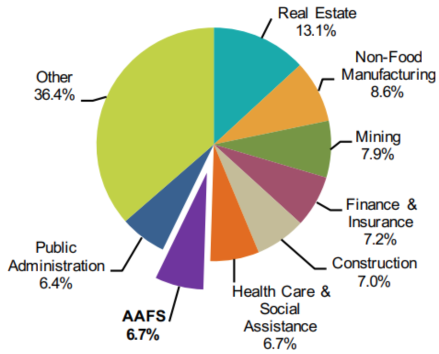
APPENDIX 1

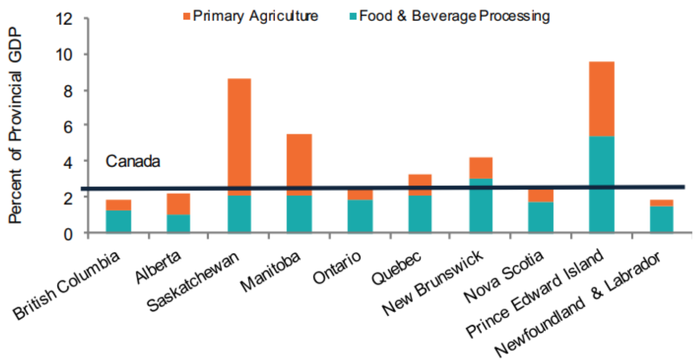
Chart B.4
Distribution of Canadian GDP by Sector, 2016



Source: Statistics Canada and AAFC calculations.
Note: Data is preliminary and subject to revisions.

SOURCE: AAFC, 2017, p.41

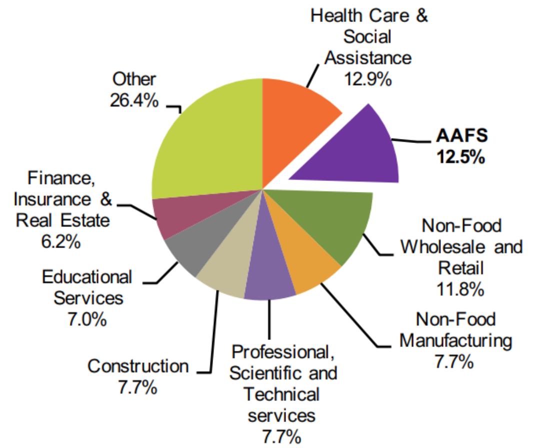
Chart B.6
Contribution of Primary Agriculture and Food and Beverage Processing to Provincial GDP, 2016



Source: Statistics Canada and AAFC calculations.
Note: Data is preliminary and subject to revisions.

SOURCE: AAFC, 2017, p.42

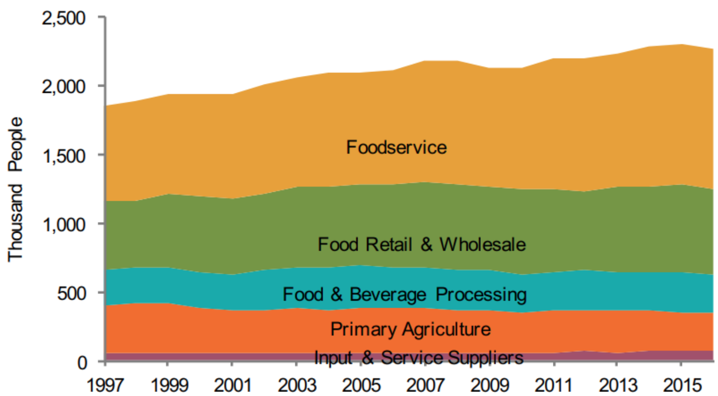
Chart B.9
Distribution of Canadian Employment by Sector, 2016



Source: Statistics Canada and AAFC calculations.
Notes: (1) Percentages may not add to 100% due to rounding. (2) See glossary for the definition of employment.

SOURCE: AAFC, 2017, p. 44

Chart B.8
Agriculture and Agri-Food System's Contribution to Canadian Employment, 1997-2016



Source: Statistics Canada and AAFC calculations.
Note: See glossary for the definition of employment.

SOURCE: AAFC, 2017, p. 44

APPENDIX 2

CLASS		Products included in category
1	a	Fluid Milk - skim, 1%, 2%, 3.25%, Egg Nogg
	b	Cream - 10%, 18%, 35%
	b1	Cream - Used in Fresh Baked Goods
	c	Innovative Fluid Milk Products
	d	Fluid Milk Sold in Canada, Outside Provinces
2	a	Yogurts
	b	Sour Cream, Ice Cream
3	a	All Cheeses Except Those in Classes 3(b), 3(c), and 3(d)
	b	Cheddar, Cream Cheese, Cheese Mixes
	c	Asiago, Colby, Feta, Gouda, Havarti, Swiss, Mozzarella
	d	Mozzarella - Used on Fresh Pizza
4	a	Butter, Milk Powder, Concentrated Milk
	a1	Non-Standardized Cheese Products
	b	Concentrated Milk
	c	Innovative Industrial Milk Products
	d	Inventories
	d1	Inventory milk for interprovincial milk movement
	m	Marginal Markets
5	a	Cheese Used in Further Processing
	b	Other Dairy Products Used in Further Processing
	c	Dairy Products Used in the Confectionery Sector
	d	Planned Exports

SOURCE: Alberta Milk, 2016, p.15

APPENDIX 3

Table 3A.1 List of key traits in dairy cattle proofs in Canada (Van Doormal, 2007; Robinson et al. 1994; Kern et al., 2014)

Attribute	Interpretation
Milk, Fat and Protein Yields	Expected yield of milk, fat and protein during a 305-day lactation in a herd of average management. Expressed in Estimated Breeding Values (EBVs)
ME kg Milk, Fat, Protein yields	Mature Equivalent units: Milk, fat and protein yield measurements for cows converted from BCA values (Breed Class Average units). MEs are calculated as [Cows yield in kg/ Avg yield for age and month] x [avg yield for mature cow], (Robinson et al., 1994).
Conformation	Expected relative superiority of the first lactation daughters for each type trait (composite measure for stature, top line, weight, chest width, body depth and loin strength (Kern et al., 2014))
Mammary System	The quality for an animal's mammary system. It makes up for 40% of the relative merit of a Holstein cow in their Score Card. (composite measure for udder depth, udder texture, udder cleft (Kern et al., 2014).
Feet and Legs	The quality for an animal's feet and legs. It makes up for 25% of the score of a Holstein Score Card.
Daughter Fertility (DF)	Represents expected genetic potential of a sire's daughters for fertility evaluated across all lactations. Will include age at 1st insemination of virgin heifers; their non-return rate at 56 days; the interval between calving and 1st insemination for cows and; non-return rate for cows at 56 days.
Somatic Cell Score (SCS)	Expected score of daughters in their first 3 lactations. A lower count indicates more resistance for mastitis. Under 3.0 is desirable.
Herd Life	The expected amount of additional lactations after involuntary culling as compared to the average bull, regardless of production levels
Active Days	Days in which semen sample was available for purchase
Total Insemination	Total number of individual semen samples purchased

Table 3A.2 List of type traits and associated Heritabilites (CDN, 2000)

Type Trait	Range in Scores	Heritability (%)
Conformation (Final Score)	Under 60 - Over 90	32
Dairy Character	Poor 1 - Ex 3	30
Frame / Capacity	Poor 1 - Ex 3	41
Rump	Poor 1 - Ex 3	24
Feet & Legs	Poor 1 - Ex 3	21
Fore Udder	Poor 1 - Ex 3	28
Rear Udder	Poor 1 - Ex 3	26
Mammary System	Poor 1 - Ex 3	29
Size	1 - 9 (measured)	37
Stature	1 - 9 (measured)	53
Height at Front End	1 - 9	25
Chest Width	1 - 9	27
Body Depth	1 - 9	32
Loin Strength	1 - 9	25
Pin Width	1 - 9 (measured)	34
Pin Setting (Desirability)	1 - 5 (measured)	43
Rump Angle	1 - 9 (measured)	43
Bone Quality	1 - 9	28
Foot Angle	1 - 9	13
Set of Rear Legs (Desirability)	1 - 5	26
Rear Legs Side View	1 - 9	26
Udder Depth	1 - 9 (measured)	39
Udder Texture	1 - 9	17
Median Suspensory	1 - 9 (measured)	15
Fore Attachment	1 - 9	27
Fore Teat Placement	1 - 9	31
Fore Teat Length	1 - 9 (measured)	30
Rear Attachment Height	1 - 9 (measured)	24
Rear Attachment Width	1 - 9 (measured)	24

APPENDIX 4

Table 4.A1 Tobit results for Baseline model (a)

	2008		2009		2010		2011		2012		2013		2014		2015		2016		2008-2016
Variable	JAN-JULY	AUG-DEC	JAN-JULY	AUG-DEC	JAN-JULY	AUG-DEC	JAN-JULY	AUG-DEC	JAN-JULY	AUG-DEC	JAN-JULY	AUG-DEC	JAN-JULY	AUG-DEC	JAN-JULY	AUG-DEC	JAN-JULY	AUG-DEC	PANEL
constant	65.69	-19.962	98.546**	136.136**	107.881**	94.645**	80.916**	110.414**	91.534**	97.142**	62.566*	16.191	5.073	-26.771	-6.864	-6.214	4.532	-3.778	9.433
	(108.486)	(89.623)	(42.919)	(41.779)	(34.977)	(38.698)	(37.966)	(40.794)	(39.512)	(38.586)	(37.352)	(38.293)	(38.942)	(40.301)	(37.494)	(37.078)	(34.321)	(47.027)	(14.885)
EBV Milk	0.013	0.007	-0.006	-0.004	-0.004	-0.007**	-0.005*	-0.008**	-0.007	-0.009**	-0.009**	-0.009**	-0.009**	-0.008**	-0.004	-0.002	-0.003	0.006	-0.003**
	(0.010)	(0.008)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.001)
EBV Fat	0.458**	0.665***	0.231**	0.154**	0.101*	0.091	0.125**	0.219***	0.169**	0.172**	0.118*	0.124**	0.094	0.086	0.008	-0.067	-0.025	-0.050	0.059**
	(0.175)	(0.149)	(0.068)	(0.064)	(0.054)	(0.595)	(0.058)	(0.062)	(0.060)	(0.0610	(0.060)	(0.060)	(0.062)	(0.066)	(0.060)	(0.062)	((0.059))	(0.082)	(0.024)
EBV Protein	-0.970*	-0.721**	-0.024	0.006	0.070	0.119	0.043	0.066	0.034	0.052	0.070	0.038	0.035	-0.017	-0.088	-0.121	-0.120	-0.237	0.030
	(0.413)	(0.313)	(0.134)	(0.122)	(0.099)	(0.113)	(0.108)	(0.110)	(0.107)	(0.109)	(0.108)	(0.108)	(0.113)	(0.122)	(0.115)	(0.118)	(0.111)	(0.161)	(0.045)
Conf	4.142*	4.994**	1.913**	0.829	0.605	0.151	-0.496	-0.467	-0.523	-1.058	-0.409	0.003	0.553	0.872	0.125	0.422	0.889	1.095	1.187***
	(2.021)	(1.555)	(0.770)	(0.691)	(0.579)	(0.633)	(0.622)	(0.681)	(0.670)	(0.700)	(0.688)	(0.697)	(0.703)	(0.764)	(0.726)	(0.750)	(0.702)	(0.976)	(0.283)
Mammary System	-0.510	-0.409	0.850	1.256**	1.008*	1.720**	1.443**	1.293**	1.005*	1.462**	0.210	-0.098	-0.708	-0.874	0.063	-0.400	-1.137*	-1.370	-0.004
	(1.718)	(1.325)	(0.668)	(0.623)	(0.512)	(0.559)	(0.546)	(0.609)	(0.593)	(0.615)	(0.602)	(0.612)	(0.624)	(0.678)	(0.640)	(0.671)	(0.641)	(0.909)	(0.250)
Feet and Legs	0.195	-0.182	-0.482	-0.286	0.069	0.259	0.817**	1.077**	1.109**	1.24**	1.433***	1.281**	1.438***	1.422**	1.106**	1.306**	1.212**	1.351**	0.995***
	(1.077)	(0.832)	(0.444)	(0.415)	(0.335)	(0.360)	(0.340)	(0.359)	(0.356)	(0.361)	(0.365)	(0.373)	(0.387)	(0.420)	(0.399)	(0.416)	(0.381)	(0.535)	(0.156)
DF	-0.917	-0.536	-1.45***	-1.461***	-1.304***	-1.193***	-1.177***	-1.552***	-1.336***	-1.613***	-1.192***	-0.891**	-0.747**	-0.342	-0.370	-0.155	-0.091	-0.219	-0.429***
	(0.852)	(0.732)	(0.346)	(0.329)	(0.273)	(0.298)	(0.293)	(0.312)	(0.296)	(0.293)	(0.279)	(0.282)	(0.281)	(0.290)	(0.268)	(0.268)	(0.246)	(0.339)	(0.107)
SCS	-11.669	2.514	5.205	-5.524	-0.183	-1.226	4.186	5.793	6.397	14.628**	13.905*	19.811**	18.561**	15.075**	11.572*	4.908	0.441	5.350	5.743*
	(18.017)	(14.696)	(6.921)	(6.657)	(5.544)	(6.199)	(6.171)	(6.486)	(6.501)	(6.428)	(6.451)	(6.591)	(6.759)	(7.132)	(6.583)	(6.660)	(6.294)	(8.940)	(2.654)
N	387	458	956	1050	1410	1456	1594	1603	1758	1780	2033	2088	2246	2190	2252	2224	2224	1727	7799
LL	-488.41	-680.77	-2101.18	-2365.01	-3194.73	-3264.93	-3496.65	-3582.53	-3967.41	-4032.43	-4741.50	-4836.27	-5096.48	-5033.0	-5280.75	-5379.23	-5628.12	-4382.999	-22428.45

*=α significant at 10%, **=α significant at 5%, ***=α significant at 99% | Statistically significant values are bold | Standard deviations provided in parentheses | LL = Log Likelihood value

Table 4.A2 Tobit results, Model without Protein (c)

	2008		2009		2010		2011		2012		2013		2014		2015		2016		2008-2016
Variable	JAN-JULY	AUG-DEC	JAN-JULY	AUG-DEC	JAN-JULY	AUG-DEC	JAN-JULY	AUG-DEC	JAN-JULY	AUG-DEC	JAN-JULY	AUG-DEC	JAN-JULY	AUG-DEC	JAN-JULY	AUG-DEC	JAN-JULY	AUG-DEC	PANEL
constant	66.505	-21.379	98.612**	136.126**	106.924**	90.850**	78.789**	106.452**	89.735**	13.703	58.809	13.703	2.579	-25.841	-2.787	-1.813	7.198	-0.535	8.167
	(109.606)	(89.837)	(42.919)	(41.777)	(34.945)	(38.537)	(37.570)	(40.228)	(39.084)	(37.613)	(36.891)	(37.613)	(38.085)	(39.732)	(37.134)	(36.858)	(34.258)	(47.026)	(14.762)
EBV Milk	-0.008	-0.009*	-0.006**	-0.004*	-0.003	-0.004**	-0.004**	-0.007**	-0.006**	-0.008***	-0.007***	-0.008***	-0.008***	-0.008***	-0.006**	-0.004**	-0.005**	0.001	-0.002**
	(0.005)	(0.005)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.001)
EBV Fat	0.259*	0.508***	0.226***	0.156**	0.117**	0.118**	0.135**	0.237***	0.179**	0.135**	0.139**	0.135**	0.104**	0.082	-0.015	-0.098*	-0.058	-0.117*	0.067**
	(0.152)	(0.129)	(0.060)	(0.057)	(0.049)	(0.054)	(0.051)	(0.054)	(0.052)	(0.051)	(0.051)	(0.051)	(0.052)	(0.057)	(0.053)	(0.054)	(0.050)	(0.068)	(0.021)
EBV Protein																			
Conf	5.345**	5.522***	1.938**	0.823	0.553	0.072	-0.520	-0.492	-0.539	-0.019	-0.464	-0.019	0.539	0.878	0.151	0.425	0.870	1.052	1.178***
	(2.009)	(1.551)	(0.758)	(0.679)	(0.574)	(0.628)	(0.619)	(0.679)	(0.668)	(0.694)	(0.683)	(0.694)	(0.701)	(0.763)	(0.726)	(0.751)	(0.703)	(0.977)	(0.283)
Mammary System	-1.600	-1.065	0.828	1.262**	1.058**	1.798**	1.462**	1.311**	1.016*	-0.078	0.256	-0.078	-0.694	-0.880	0.042	-0.392	-1.114*	-1.320	0.004
	(1.696)	(1.309)	(0.656)	(0.611)	(0.507)	(0.554)	(0.544)	(0.607)	(0.591)	(0.609)	(0.598)	(0.609)	(0.623)	(0.677)	(0.640)	(0.671)	(0.641)	(0.909)	(0.250)
Feet and Legs	-0.157	-0.250	-0.488	-0.284	0.087	0.276	0.824**	1.081**	1.115**	1.294***	1.457***	1.294***	1.445***	1.419**	1.086**	1.288**	1.208**	1.342**	1.003***
	(1.072)	(0.835)	(0.443)	(0.413)	(0.334)	(0.360)	(0.340)	(0.359)	(0.355)	(0.371)	(0.363)	(0.371)	(0.387)	(0.420)	(0.399)	(0.416)	(0.381)	(0.536)	(0.155)
DF	-0.768	-0.388	-1.449***	-1.461***	-1.313***	-1.184***	-1.165***	-1.524***	-1.323***	-0.875**	-1.171***	-0.875**	-0.729**	-0.349	-0.407	-0.207	-0.130	-0.290	-0.418***
	(0.858)	(0.732)	(0.346)	(0.329)	(0.273)	(0.298)	(0.292)	(0.308)	(0.293)	(0.278)	(0.278)	(0.278)	(0.275)	(0.285)	(0.264)	(0.264)	(0.244)	(0.336)	(0.106)
SCS	-18.052	-2.369	5.135	-5.512	0.522	-0.087	4.579	6.276	6.625	20.155**	14.548**	20.155**	18.829**	14.991**	11.293*	4.932	0.643	6.198	5.827**
	(18.194)	(14.596)	(6.910)	(6.641)	(5.452)	(6.103)	(6.090)	(6.433)	(6.459)	(6.517)	(6.375)	(6.517)	(6.702)	(7.106)	(6.577)	(6.666)	(6.295)	(8.930)	(2.651)
N	387	458	956	1050	1410	1456	1594	1603	1758	2088	2033	2088	2246	2190	2252	2224	2224	1727	7799
LL	-491.28	-683.52	-2101.20	-2365.01	-3194.98	-3265.49	-3496.73	-3582.71	-3967.46	-4836.33	-4741.71	-4836.33	-5096.52	-5033.01	-5281.04	-5379.76	-5628.70	-4384.08	-22428.67

*=α significant at 10%, **=α significant at 5%, ***=α significant at 99% | Statistically significant values are bold | Standard deviations provided in parentheses | LL = Log Likelihood value

Table 4.A3 Tobit results for Panel data (2008-2016), by treatment (a-i)

	a. Baseline	b. No Fat	c. No Protein	d. No Milk	e. Only Fat	f. Only Protein	g. Only Milk	h. No Conformation	i. No Mamm. System	j. Herd Life included
constant	9.433	12.925	8.167	5.698	6.726	9.078	9.915	18.195	9.446	**77.094*** **
	(14.885)	(14.815)	(14.762)	(14.769)	(14.754)	(14.709)	(14.748)	(14.749)	(14.858)	(19.741)
EBV Milk	**-0.003** **	**-0.003** **	**-0.002** **	n/a	n/a	n/a	-0.0003	**-0.002***	**-0.003*** **	**-0.003** **
	(0.001)	(0.001)	(0.001)	n/a	n/a	n/a	(0.001)	(0.001)	(0.001)	(0.001)
EBV Fat	**0.059** **	n/a	**0.067** **	**0.062** **	**0.037** **	n/a	n/a	**0.067** **	**0.059***	**0.058** **
	(0.024)	n/a	(0.021)	(0.024)	(0.017)	n/a	n/a	(0.024)	(0.024)	(0.024)
EBV Protein	0.030	**0.086** **	n/a	-0.040	n/a	0.013	n/a	0.021	0.030	0.051
	(0.045)	(0.039)	n/a	(0.029)	n/a	(0.020)	n/a	(0.045)	(0.045)	(0.045)
Conformation	**1.187*** **	**1.246*** **	**1.178*** **	**1.155*** **	**1.157*** **	**1.215*** **	**1.243*** **	n/a	**1.183*** **	**0.964** **
	(0.283)	(0.282)	(0.283)	(0.283)	(0.283)	(0.282)	(0.282)	n/a	(0.138)	(0.286)
Mammary System	-0.004	-0.035	0.004	0.001	-0.022	-0.032	-0.021	**0.914*** **	n/a	0.336
	(0.250)	(0.250)	(0.250)	(0.250)	(0.250)	(0.250)	(0.249)	(0.122)	n/a	(0.260)
Feet and Legs	**0.995*** **	**1.019*** **	**1.003*** **	**1.030*** **	**1.032*** **	**1.059*** **	**1.064*** **	**1.384*** **	**0.996*** **	**1.135*** **
	(0.156)	(0.155)	(0.155)	(0.155)	(0.155)	(0.154)	(0.154)	(0.126)	(0.147)	(0.159)
DF	**-0.429*** **	**-0.426*** **	**-0.418*** **	**-0.391*** **	**-0.395*** **	**-0.384*** **	**-0.381*** **	**-0.535*** **	**-0.43*** **	-0.034
	(0.107)	(0.107)	(0.106)	(0.106)	(0.106)	(0.106)	(0.105)	(0.105)	(0.105)	(0.130)
SCS	**5.743***	**4.553***	**5.827** **	**5.688** **	**5.364** **	**4.423***	4.235	**6.535** **	**5.749** **	-1.054
	(2.654)	(2.608)	(2.651)	(2.654)	(2.645)	(2.607)	(2.603)	(2.650)	(2.625)	(2.988)
HL	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	**-0.852*** **
	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	(0.161)
N	7799	7799	7799	7799	7799	7799	7799	7799	7799	7739
LL	-22428.45	-22431.40	-22428.67	-22430.47	-22431.45	-22433.77	-22433.85	-22437.26	-22428.45	-22355.83

*=α significant at 10%, **=α significant at 5%, ***=α significant at 99% | Statistically significant values are bold | Standard deviations provided in parentheses | LL = Log Likelihood value