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THE ECONOMICS OF MILK QUALITY MANAGEMENT PRACTICES AND MILK PRICING IN SIMULATED UNITED STATES DAIRY HERDS

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THE ECONOMICS OF MILK QUALITY MANAGEMENT PRACTICES AND MILK PRICING IN SIMULATED UNITED STATES DAIRY HERDS

DISSERTATION

A dissertation submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in the College of Agriculture, Food and Environment at the University of Kentucky

By

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2020

ABSTRACT OF DISSERTATION

THE ECONOMICS OF MILK QUALITY MANAGEMENT PRACTICES AND MILK PRICING IN SIMULATED UNITED STATES DAIRY HERDS

Mastitis is considered one of the most common and costly diseases in the dairy industry. Intramammary infection status at a herd level is measured using somatic cell count (SCC). Understanding the total cost of an elevated somatic cell count can help influence dairy farmers to lower SCC and select management practices to produce higher quality milk. The first objective of our research was to determine if the cost of an elevated somatic cell count to farms can be decreased through the adoption of management practices with varying expenses. Using stochastic simulation modeling, the adoption of three differently priced management practices were modeled in herds with varying somatic cell counts. Results were highly dependent on whether a premium scheme for lower SCC milk was in place and how close a herd's initial SCC was to a premium level. When herd SCC reduced enough to receive a premium, the total cost of SCC to the farm was dramatically reduced.

One management practice that has historically been used in the industry is treating every quarter of every cow with an intramammary antibiotic at the end of her lactation. However, future restrictions of antibiotic use in animal agriculture may pressure dairy farmers to treat only cows with an intramammary infection at the end of the lactation. The second objective of our research was to complete an economic analysis comparing the total cost of dry cow therapy in simulated dairy farms when every quarter of every cow was treated with intramammary antibiotics compared treating only cows with an intramammary infection at end of the lactation. Results from the model indicate the treating every quarter of every cow at the end of lactation was most economically feasible in simulated farms. However, as the cost of a case of mastitis and mastitis incidence decrease, treating only cows with an intramammary infection may become economically feasible.

Within recent years, the dairy industry in the Southeastern United States has shown interest in changing the way milk is priced. Currently, dairy farmers in the Southeast are paid for total fluid volume and butterfat, while other areas are paid for milk fat, protein, and other solids yields. The third objective of our research was to determine the differences in milk value using the conventional milk pricing system compared to a multiple component pricing system using cow production records. After examining average milk values, multiple component pricing may result in Southeastern dairy farmers being paid more for their milk.

KEYWORDS: stochastic modeling, somatic cell count, dry cow therapy, multiple component pricing, dairy cattle

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2/12/2020

Date

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REVIEW OF LITERATURE

INTRODUCTION

The dairy industry has experienced many changes within the past ten years. While the number of dairy farms in the United States **(US)** has decreased, the number of total cows has steadily increased (USDA National Agricultural Statistics Service, 2017). Cow numbers, along with more efficient milk production has resulted in more milk on the market. Because of the large quantity of milk on the market, dairy processors and co-ops have become more selective of milk quality requirements (Nickerson, 2012, Nolan, 2018). One measure processors use to determine milk quality at a herd level is somatic cell count **(SCC)**. Though some are still offered, premiums for SCC are becoming a rarity and quality is to be expected (Nickerson, 2012, Nolan, 2018). The demand for quality milk adds pressure to farmers to make sure they have management practices in place to meet milk quality expectations.

Dry cow therapy, or treatment of cows with intramammary antibiotics **(IMMA)** at the end of the lactation, is used by farmers to treat intramammary infections **(IMI)** at the end of lactation and prevent new infections in the dry period. However, pressure is being put on policymakers to decrease the use of antibiotics in animal agriculture (Croney et al., 2012). The use of dry cow therapy as a preventative measure is no longer allowed in some countries (Lam et al., 2017, McDougall, 2018).

As changes in the dairy industry continue, use of management practices to maintain the production of high-quality milk while maintaining efficiency is magnified. The objectives of this literature review are to discuss 1) the importance of somatic cell count **(SCC)** as a milk quality indicator, 2) the economics of herd SCC, 3) the efficacy and economics of different dry cow therapy schemes, and 4) how milk pricing options may affect the profitability of dairy farmers.

SOMATIC CELLS

Role of Somatic Cells

A large variety of body cells exist in the mammary gland. However, concern arises in the dairy industry when white blood cells are present at high amounts in milk. White blood cells are present at higher amounts in the mammary gland during an infection. Somatic cells primarily consist of polymorphonuclear neutrophils leukocytes **(PMN)**, macrophages, and lymphocytes (Harmon, 1994). No matter the infection status of the mammary gland, each of these cells always exist in milk. The type of cells that exists changes based on whether the gland is infected. In a healthy mammary gland, most white blood cells present in the milk consist of macrophages (15% to 40%) and lymphocytes (54% to 80%) (Rivas et al., 2001, Alhussien and Dang, 2018). Macrophages and lymphocytes may eliminate some microorganisms that enter the gland at each milking (Kehrli and Shuster, 1994) because of an open teat end (Alhussien and Dang, 2018).

Polymorphonuclear neutrophils range from 0 to 7% of the cells in milk when the mammary gland is healthy (Lee et al., 1980, Rivas et al., 2001), but when the gland becomes infected PMN make up 90 to 95% of the cells in the milk (Harmon, 1994, Kehrli and Shuster, 1994). Once in the milk, microorganisms release products of metabolism that act as chemoattractants, which enroll the help of PMN (Kehrli and Shuster, 1994, Alhussien and Dang, 2018). Once recruited by an immune response, the rate at which PMN enter the mammary tissue and milk increases for 2 to 3 hours (Persson et al., 1992) and can stay elevated for greater than 150 hours (Kehrli and Shuster, 1994). Thus, an increase in the number of somatic cells in milk is associated with an IMI.

Somatic Cell Count

Prescott and Breed (1910) conducted one of the first studies to examine the count of somatic cells in milk. Previously, milk was centrifuged to separate the cream and only the non-cream (sediment) layer was tested. Prescott and Breed (1910) developed a "direct" method in which they counted somatic cells after the milk was shaken (homogenized) to distribute the cream. They concluded that by separating the cream and only testing the sediment layer, SCC was highly underestimated. The average SCC of milk tested with the sediment method was 305,000 cells/mL, while the average of the direct method on the same samples was 1,690,000 cells/mL.

Throughout the late 1900s, the automation of counting cells was developed and tested. Two common methods were the Coulter and flow cytometry methods. With the Coulter method, particles are suspended in an electrolyte solution, and the dispersion of the electrolyte solution is measured and correlated to the size of the particle. Flow cytometry works in four steps. First cells are placed into a solution. In the case of the dairy industry, cells do not have to be placed in a solution other than milk. Second, the flow cytometer takes in the solution and funnels the solution through a nozzle small enough that cells have to enter in a singular order. Then a laser is passed through each cell in the solution, and light is scattered both forward and to the side. In the final step, a histogram of both the forward and side scatter is made. By combining the histograms from the entire solution, different cell populations can be determined.

Both the Coulter and flow cytometry methods have been correlated with the direct counting method (Madsen, 1975). Other research concluded that the Coulter method might lead to over counting somatic cells because any object above a certain size is counted (Brooker, 1978, Hill et al., 1982, Hoare et al., 1982). Heald et al. (1977) concluded that the use of a Fossomatic (Foss, Hillerod, Denmark), which uses flow cytometry, was acceptable for use in Dairy Herd Information Association lab test. The Dairy Herd Improvement Association and other milk quality testing labs are still using the Fossomatic today.

Somatic cell counts can be influenced by many different variables (lactation and days in milk (**DIM)**) (Harmon, 1994, Alhussien and Dang, 2018), making cow and herd SCC data skewed with the mean being greater than the median (Ali and Shook, 1980). To analyze cow and herd SCC data from a research standpoint, a transformation of the data must be completed. Before the 1980s a geometric mean transformation was often performed. Ali and Shook (1980) concluded that a log transformation was sufficient, and adding a constant improved the transformation. Wiggans and Shook (1987) developed the following equation to log transform SCC data.

$$SCS = log_2\left(\frac{SCC}{100}\right) + 3$$

With this equation, the log transformation of SCC is known in the dairy industry today as somatic cell score (SCS). Somatic cell data can be reported to the farmer as either SCC or SCS. However, SCS is most commonly used in research analysis. Each one-point increase in SCS is equated to a doubling in SCC.

Somatic Cell Count and Intramammary Infection

Evidence proves that when a mammary gland is infected with a pathogen, SCC will increase (Schalm et al., 1964, Schalm et al., 1966, Schalm and Ziv-Silberman, 1968). The majority of the increase in cells when the mammary gland is infected are PMN (Kelly et al., 2000, Pillai et al., 2001). Differences in SCC can be observed even when clinical signs of the IMI are not present. When physical signs of the IMI are present, the IMI is considered clinical mastitis **(CM),** while subclinical mastitis **(SCM)** cannot be seen with the naked eye. In both CM and SCM, an IMI is confirmed by taking a bacteriological culture of milk from a cow. A cow is considered to have an IMI when duplicate bacteriological cultures have positive growth with the same bacteria type (Oliver et al., 2004). Because of the increase in SCC that comes with an IMI, SCC is the most common way SCM is detected.

Natzke et al. (1972) were one of the first to examine the differences in SCC between cows with a healthy mammary gland and those with an IMI based on identified bacterial pathogen. When investigating SCC a three year period the average ± standard deviation **(SD)** of cows that did not have an IMI was 214,000 ± 23,800 cells/mL while cows with an IMI had an average ± SD of 507,000 ± 94,908, 701,000 ± 150,457, and 1,470,000 ± 557,210 cells/mL if the cow had 1, 2, 3, or 4 infected quarters, respectively. While Natzke et al. (1972) were one of the first to determine the average SCC between a healthy mammary gland and one with an IMI, future research helped determine the threshold of SCC to predict whether a gland was infected.

McDermott et al. (1982) were one of the first to use SCC data to determine if IMI could be predicted at different SCC thresholds. To predict IMI status, sensitivity, specificity, and predictability were calculated using the following 5 equations:

$$(1)\ Sensitivity = \frac{TP}{TP + FN}$$

$$(2)\ Specificty = \frac{TN}{TN + FP}$$

$$(3)\ Predictability\ Positive = \frac{TP}{TP + FP}$$

$$(4)\ Predictability\ Negative = \frac{TN}{TN + FN}$$

$$(5)\ Prevalence\ of\ Infection = \frac{TP + FN}{TP + FP + TN + FN}$$

Where:

TP = true positive (bacteriological culture positive with a SCC above threshold)

FP = false positive (bacteriological culture negative with a SCC above threshold)

TN = true negative (bacteriological culture negative with a SCC below threshold)

FN = false negative (bacteriological culture positive with a SCC below threshold)

Sensitivity and specificity are often used in epidemiology and in the medical profession to measure the success of disease testing. Sensitivity is the ability of a test to correctly identify those with a disease, while specificity is the ability of the test to identify those who do not have the disease correctly.

Using the 5 equations, McDermott et al. (1982) examined SCC thresholds and concluded that 400,000 cells/mL was the optimal SCC to determine IMI. Though McDermott et al. (1982) set a threshold of 400,000 cells/mL, more recent research has repeatedly shown that a SCC of 200,000 cells/mL has been optimal to limit false positives and negatives in IMI diagnosis (Dohoo and Leslie, 1991, Schepers et al., 1997, Pantoja et al., 2009b, Shook et al., 2017, Jadhav et al., 2018). Therefore, a SCC greater than 200,000 cells/mL is associated with a cow having SCM.

Relationships besides IMI status are associated with varying SCC (Dohoo and Leslie, 1991, Harmon, 1994, Shook et al., 2017). Herd, cow, season, stage of lactation, and parity have been shown to have a relationship with SCC (McDermott et al., 1982, Kehrli and Shuster, 1994, Schepers et al., 1997, Shook et al., 2017). Though DIM and parity are associated with SCC (Harmon, 1994, Alhussien and Dang, 2018), these effects do not hold a cause and effect relationship. For example, evidence suggests that if a cow has never had an IMI, SCC does not differ from lactation to lactation (Natzke et al., 1972). For cows that never experienced an IMI, average somatic cell counts were 136,000 cells/mL, 112,000 cells/mL, and 153,000 cells/mL in their first, second and third, and fourth and greater lactations, respectively. Laevens et al. (1997) presented similar results where mean SCC were similar across lactations for cows that did not experience an IMI. However, Laevens et al. (1997) concluded that cows in their 2^{nd} and 3^{rd} lactations had an increase in SCC toward the end of lactation compared to 1^{st} parity cows.

When examining the relationship between SCC and DIM, Schepers et al. (1997) and Laevens et al. (1997) found that when graphing SCC across lactation, the SCC curve was the inverse of the milk production curve. Somatic cell count tends to start high at the beginning of the lactation, decrease to the lowest point in the mid-lactation, and increase at the end of the lactation (Harmon, 1994, Alhussien and Dang, 2018). To explain the increase in SCC that is commonly seen at the end of lactation, Green et al. (2006) suggest that this phenomenon may be due to lack of dilution.

Season of testing date has also shown to be associated with SCC (Harmon, 1994, Pantoja et al., 2009a, Shook et al., 2017). However, this should not be looked at as a cause and effect relationship either because season cannot physically affect SCC. de Haas et al. (2002) suggests that rather than the season of the year affecting SCC, cows might be more prone to IMI during certain times of the year.

Management of Herd Somatic Cell Counts

The National Mastitis Council developed a 5-point program to help farmers control mastitis (Dodd and Neave, 1970). Those points include post-milking teat disinfection **(PST)**, comprehensive dry cow therapy, therapy of clinical mastitis cases during lactation, proper milking machine maintenance, and culling cows with chronic CM or SCM. According to USDA Animal and Plant Health Inspection Service (2016), 96.8% of surveyed dairies used a PST, 89.4% use intramammary IMMA to treat mastitis, 90.8% used IMMA at dry off, and 24.0% cull cows due to mastitis. Unfortunately, little research has been conducted examining the direct effects of adoption of a particular management practice on bulk tank SCC **(BTSCC)**. However, extensive research has determined relationships between BTSCC of herds with varying BTSCC and the management practices the dairy producers have implemented through survey data (Pantoja et al., 2009b, Schewe et al., 2015, Emanuelson and Nielsen, 2017). In a review of published surveys, Dufour et al. (2011) concluded that some management practices were more frequently adopted by farmers with a lower (< 250,000 cells/mL) SCC. These included cow hygiene, the use of test disinfectants at milking, the use of coliform mastitis vaccines, and antibiotic therapy at dry off.

Hygiene. When examining the relationship between management practices and BTSCC, Barkema et al. (1998a) concluded producers with a low BTSCC (< 150,000 cell/mL) paid extra attention to hygiene of both facilities and cows. Schreiner and Ruegg

(2003) determined there was a positive linear relationship with udder hygiene and SCC. For udder hygiene scores of 1, 2, 3, and 4 (Schreiner and Ruegg, 2002), IMI rates were 7.7%, 10.0%, 10.6%, and 13.5%, respectively. When evaluating cleanliness scores, udder hygiene has a higher association with SCC compared to flank and leg hygiene scores (Sant'Anna and Paranhos da Costa, 2011). The higher association with udder hygiene, compared to flank or leg hygiene, suggests keeping the udder clean was most important measure for milk quality. Sant'Anna and Paranhos da Costa (2011) concluded that cows with a very clean or clean udder had a significantly lower ($P < 0.05$) SCC than those with a very dirty udder.

Teat Disinfectant. Barkema et al. (1998a) indicated that the use of a PST was one of the most important factors between herds with a low herd SCC (< 150,000 cells/mL) and other herds ($P = 0.0007$). Farms that used a PST were 1.14 more times as likely to have a herd SCC < 150,000 cells/mL versus a herd SCC between 150,000 and 250,000 cells/mL. When used correctly, PST can decrease new IMI by 50% (Pyorala, 2002). The use of a dip cup rather than a sprayer was also more frequently adopted by farmers with a lower (< 250,000 cells/mL) herd SCC (Jayarao et al., 2004).

Coliform Bacteria Vaccinations. Early efficacy trials of an *Escherichia coli* J5 mastitis vaccination concluded that the use of a vaccine might not lower IMI rates but would decrease the severity, SCC, and signs of CM (Hogan et al., 1992a, Hogan et al., 1992b, Hogan et al., 1995b). Though efficacy trials have been completed to show the benefits of coliform mastitis vaccinations at a cow level (Hogan et al., 1992a, Hogan et al., 1992b, Hogan et al., 1995a), authors found little research that has been done examining the effect of vaccination adoption on herd SCC. In a study using 2002

National Animal Health Monitoring System data, Wenz et al. (2007) concluded that only 49.5% of farmers surveyed were utilizing a coliform vaccine and those farms that had not adopted the vaccination were 1.65 times as likely to have a high BTSCC (> 400,000 cells/mL).

Antibiotic Treatment at Dry Off. Over 80% of farms that had a majority of their cows with a SCC < 200,000 cells/mL, treated every cow with intramammary antibiotics at dry off (Hutton et al., 1990). Barkema et al. (1998a) found that 93.2% of surveyed farms with a low SCC (< 150,000 cells/mL) treated all cows at dry off. Only 76.4% of surveyed farms with a high SCC (251,000 to 400,000 cells/mL) had used intramammary antibiotics on all cows at dry off (Barkema et al., 1998a). Dufour et al. (2011) concluded that the use of intramammary antibiotics on all cows at dry off was one of the most important management practices to improve milk quality.

Overall Management. The review completed by Dufour et al. (2011) suggests that many studies have found that farms with low SCC have adopted many of the same management practices. Those practices included milkers wearing gloves, post milk teat disinfection, blanket dry cow therapy, and cleanliness of lactating cow housing and cow hygiene. However, their review also found the relationship between herd SCC and adoption of certain management practices were not repeatable from study to study. The large variation in results suggests the relationship between management practice implementation and herd SCC is very complex. More research is needed on how herd SCC changes before and after management practice adoption.

Somatic Cell Count and Milk Yield

The main cost of both CM and SCM is due to milk income loss (Shim et al., 2004, Bar et al., 2008b, Sadeghi-Sefidmazgi et al., 2011, Liang et al., 2017). Many studies have shown the negative relationship between an increase in SCC and decrease milk yield (Raubertas and Shook, 1982, Jones et al., 1984, Hadrich et al., 2018). Raubertas and Shook (1982) were one of the first to examine the effect of SCC on milk yield and concluded that the effect of SCC on milk yield was curvilinear with a 134, 286, 271, and 223 kg per lactation decrease in milk yield for lactations 1, 2, 3, and 4, respectively, for a one-unit increase in SCS. When comparing the lactation effect, primiparous cows had 50% of the production loss of multiparous cows. When examining losses on a per-day basis, Bartlett et al. (1990) concluded that a loss of 1.18 to 2.37 kg of milk was lost per day with a one-unit increase in SCS for second and higher parities, while parity one cows lost an average of 1.17 kg of milk per day.

More recent research has provided insights into the relationship between SCC and milk production. When comparing across cows with similar SCC, cows with higher milk production lost a greater percentage of total milk yield throughout their lactation (Hand et al., 2012). The same relationship was seen for cows with a consistently high SCC. Though a SCC 200,000 cells/mL has been used to determine IMI status, milk yield loss may occur at SCC less than 200,000 cells/mL (Raubertas and Shook, 1982, Bartlett et al., 1990, Nolan, 2017, Hadrich et al., 2018). Milk yield losses were greater in cows that had consecutive test day SCC greater than 100,000 cells/mL. The more test days in which SCC was greater than 100,000 cells/mL, the greater the milk loss throughout the lactation (Hadrich et al., 2018).

Management Costs

Cost of Poor Milk Quality. Estimates for the cost of mastitis have been modeled extensively (Shim et al., 2004, Huijps et al., 2008, Steeneveld et al., 2011, Rollin et al., 2015, Liang et al., 2017). Average costs per case of mastitis have ranged from (all in 2019 US$) $213.84 (Bar et al., 2008b) to $481.82 (Rollin et al., 2015). When compared against multiple cost variables, milk loss contributes the most toward the total costs of mastitis (41 to 66%) (Shim et al., 2004, Huijps et al., 2008, Sadeghi-Sefidmazgi et al., 2011, Liang et al., 2017). Treatment decisions (extended or label therapies) (Steeneveld et al., 2011) and cow characteristics (Bar et al., 2008b) have effects on the variation of the cost. Costs per CM case ranged from $244.17 to $298.43 when treated with the label and extra-label (extended therapy) treatment strategies, respectively (Steeneveld et al., 2011). Depending on cow traits, such as parity, DIM, and milk production, costs of mastitis could be as high as $481.44 per case (Bar et al., 2008b). However, when cows are expected to be culled for reasons other than mastitis, costs of mastitis cases could be as low as $3.58/mastitis case (Bar et al., 2008b). For example, for a cow with CM that is in late lactation that is expected to be culled for lameness reasons and low milk production, the cost of culling is split among the different reasons for culling.

Cost of Culling. The estimation of culling costs in animal health economics has been done using retention payoff value **(RPO)** (Dijkhuizen and Morris, 1997). Often the cost of culling is oversimplified by taking the slaughter value of the cull cow minus the cost of her replacement (Bewley et al., 2010). However, RPO takes into account the future value of the cull cow compared to the future value of her replacement. The optimal time to cull the cow from the herd is when her RPO reaches 0 (Dijkhuizen and Morris, 1997). Any value of above 0 should be considered an opportunity cost for her, and when the RPO is below 0, money is being lost by not replacing the animal with a more profitable one (Dijkhuizen and Morris, 1997). T

Troendle et al. (2017) also concluded that the cost of culling associated with SCC is oversimplified. Culling benefit estimation for SCC is simplified to the benefit gained from culling a top contributor to a herd's BTSCC to reach a SCC in which the processor will either pay a premium or remove a penalty minus the cost of culling the cow. However, Troendle et al. (2017) stated that the value of the replacements needs to be taken into account as well. When taking into account the value of the cull cow's replacement, producers could increase their annual profit from $786.00 to $8,301 (Troendle et al., 2017).

Cost of Disease

The cost of a case of mastitis has been extensively researched using stochastic simulation modeling (Bennett, 1992, Swinkels et al., 2005, Bewley et al., 2010, Halasa et al., 2010, van den Borne et al., 2010, Steeneveld et al., 2011, Liang, 2013, Rollin et al., 2015, Liang et al., 2017, Nolan, 2017). McInerney et al. (1992) stated that economic studies of disease have mainly focused on the costs due to particular diseases, and by determining the total cost of the disease, more information is provided for the farmer to make a decision. McInerney et al. (1992) further explained that the cost of disease is made up of two parts: the output losses from the disease and expenditures for disease prevention and treatment.

The cost of disease can be broken down into a simple equation (McInerney et al., 1992):

$$C = L + E$$

Where:

C = the total cost of the disease

L = losses or benefits taken away, (i.e., losses in milk production or losses in premiums)

E = expenses used to manage the disease (i.e., veterinarian costs, drugs for treatment, preventative management costs)

Though Hogeveen and Van Der Voort (2017) agree with the equation and theory explained by McInerney et al. (1992), they consider the losses to be failure costs. These failure costs should not only consider milk production losses but any losses in income from the disease such as veterinary costs and costs for treatment of the disease. McInerney et al. (1992) consider these to be losses. Hogeveen and Van Der Voort (2017) consider expenses to be preventative costs, which are associated with measures to prevent disease (increased labor, vaccinations, or disinfectants).

The equation above can also be explained in a graphical form known as a Loss-Expenditure Frontier, as depicted in Figure 1.1 (McInerney et al., 1992). The axes of the graph portray annual financial sums for losses (x-axis) and expenditures (y-axis). If no actions are taken to control a disease, maximum losses, L in Figure 1.1, are experienced. Below the point of L, as more management practices are added, and the expenditures increase, losses from the disease decrease. The curve of the total cost (Figure 1.1) slopes downward at a diminishing rate, meaning for each additional dollar spent on disease management, the financial value of reduced losses becomes smaller (McInerney et al., 1992).

The point where L_A intersects with E_A in Figure 1.1 represents the technical optimum for the cost of disease. Because most diseases cannot be eradicated, there comes the point in which the losses from a disease cannot get any lower (L_A in Figure 1.1). For this reason, any expenses past E_A is not necessary.

Because both axes are scaled in monetary value, the point where losses + expenditures are at a minimum occurs at point M in Figure 1.1. The point where L_M and E_M meet represents the economic optimum or the point where $1 invested in the management of a disease will return a $1 in reduced losses (McInerney et al., 1992).

With over 200 citations, the theory presented by McInerney et al. (1992) has been used frequently to calculate the cost of disease in livestock. However, as argued by Hogeveen and Van Der Voort (2017), most of the research being completed with a focus in milk quality are only calculating the failure costs (losses and the costs of treatment). Little research has been conducted examining optimal management schemes.

McInerney et al. (1992) used the theory presented above to determine the economic benefit of investing in three different management practices to control mastitis. Management practices examined were the use of a teat disinfectant, DCT, and testing milking machines for proper function. McInerney et al. (1992) concluded that mastitis had the least economic impact ($7,071.78/ farm per year in 2019 US$) on farms that adopted and used these procedures on all cows or year-round. Benefits from adoption included increased milk production and increased premiums for higher quality milk.

DRY COW MANAGEMENT

The Dry Period

The dry period is the time in the lactation cycle in which the cow is no longer producing milk. Three stages define the dry period (Hurley, 1989). The first is involution, which is the time in which the mammary gland switches from lactating to non-lactating. During the involution period, the mammary epithelial cells regress. The second stage is considered a steady state in which the mammary tissue is not producing milk. Finally, the redevelopment state is when the mammary gland starts producing colostrum in preparation of parturition (Hurley, 1989). The dry period is important because, through these three stages, the mammary gland replicates epithelial cells and repairs damage (Capuco et al., 1997). If cows are continuously milked and not given a break between calvings, the mammary gland cannot replace damaged epithelial cells. Cow with dry periods lasting less than 35 days run the risk of the mammary tissue not repairing damage which can lead to reduced milk production in the next lactation (Capuco et al., 1997).

Risk of New Intramammary Infections

The dry period is also an important time for the management of the cow because it is the riskiest time for new IMI (Neave et al., 1950). New IMI are 6.25 more likely in the first 21 days of the dry period than they are throughout the whole previous lactation (Neave et al., 1950). Within the same lactation, IMI are 4 times as likely to occur within the first 15 days of the lactation than any other 15 day time period throughout the lactation (Erb et al., 1984). Todhunter et al. (1991) and Taponen et al. (2007) have presented similar results, concluding that the dry period and the first two weeks of the lactation are the most likely times IMI occurs. More recent research has shown that a cow’s SCC throughout the previous lactation may be associated with the risk of IMI during the dry period (Pantoja et al., 2009a, Henderson et al., 2016).

By examining infection rates over the dry period, Pantoja et al. (2009a) concluded that cows that had a chronic infection (SCC over 200,000 cells/mL both at the time of dry off and calving) had increased CM rates (2.7 times) compared to those that had a SCC < 200,000 cells/mL at calving. Cows that had a SCC > 200,000 at dry off had a greater risk of having CM at calving. Cows that had a SCC > 200,000 cells/mL at dry off and at calving had a greater risk of developing a CM case with the first 120 days in milk (Pantoja et al., 2009a).

Research also suggests that the SCC throughout the previous lactation affected the risk of IMI through the dry period (Henderson et al., 2016). Cows that had less than 25% (of a minimum of 5 test days) of their test day SCC above 200,000cells/mL throughout their lactation are more likely to cure an IMI over the dry period than those that had greater than 75% of their test day SCC over 200,000 cells/mL. If cows had less than 25% of their test day SCC above 200,000 cells/mL they were also less likely to develop a new IMI during the dry period (Henderson et al., 2016). This evidence suggests that both the SCC at dry off and throughout the lactation should be considered when making dry cow therapy decisions.

Dry Cow Therapy

The use of IMMA at dry off is for two main reasons 1) to cure any existing IMI and 2) to prevent new IMI from occurring during the dry period. When polled by the National Animal Health Monitoring System, only 9.2% of the surveyed dairy farmers in the U.S. do not use any IMMA at the time of dry off (USDA Animal and Plant Health Inspection Service, 2016). Those that do use IMMA, two management types are used, either blanket dry cow therapy **(BDCT)** or selective dry cow therapy **(SDCT)**. In a BDCT scheme, all quarters of all cows are treated with IMMA at dry off. When using SDCT, not all quarters of all cows are treated with IMMA. Treatment is determined at a cow or quarter level based on IMI status. With a SDCT scheme, some cows may not receive IMMA at all. In the U.S., 80.3% of surveyed dairy producers use BDCT compared to 10.6% that use some form of SDCT. Of the 10.6% of survey producers that used SDCT, 6% used IMMA on 1 to 33% of their cows, 1% of farmers treated 34% to 66%, and 3.5% of farmers treated 67% to 99% of their cows with IMMA at dry off (USDA Animal and Plant Health Inspection Service, 2016).

Efficacy of Dry Cow Therapy

Blanket Dry Cow Therapy versus no Dry Cow Therapy. Pearson (1950) was one of the first to complete a study determining the effects of DCT when addressing concerns of IMI in non-lactating cows over the summer months. Later studies worked on the development of an IMMA that would last over several weeks during the dry period (Smith et al., 1967a, Smith et al., 1967b), and BDCT became a recommendation for mastitis control (Dodd and Neave, 1970). Since these early studies BDCT has repeatedly shown to decrease the incidence rate of IMI during the dry period and at calving (Schukken et al., 1993, Hogan et al., 1994, Hogan et al., 1995a, Bradley and Green, 2001, Berry and Hillerton, 2002).

More recently, Halasa et al. (2009b, 2009c) completed a meta-analysis of 36 papers to determine the effect of different dry cow therapy strategies on the ability to cure existing IMI and prevent new IMI. The overall cure rate regardless of therapy management was 78%. Quarters that were treated with an IMMA were 1.78 times more likely to have a cure success compared to those that were not treated (Halasa et al., 2009b). When it came to preventing new infections, Halasa et al. (2009c) concluded that DCT was more protective than no DCT. However, this differed based on bacterial type.

Quarters treated with IMMA were 0.62 and 0.39 times less at risk of developing a *Staphylococcus aureus* and *Streptococcus* species IMI, respectively, than those not treated. The effect of DCT on the development of a new IMI due to coliforms was not significant. More recent research agrees that bacteria type may affect DCT success (Vasquez et al., 2018).

Blanket versus Selective Dry Cow Therapy. The objective of SDCT is to reduce the IMMA use by only treating cows that have an IMI rather than using IMMA as a preventative measure. So, for SDCT to be successful, the selection criteria used to treat cows is very important. Rindsig et al. (1978) were one of the first to compare BDCT and SDCT. To select cows that would receive IMMA at dry off, they used a history of CM, results from a California Mastitis Test, and cows having a SCC over 500,000 cells/mL. Since then, the California Mastitis Test (Poutrel and Rainard, 1981), mastitis history (Schultze, 1983), SCC data (Torres et al., 2008, Scherpenzeel et al., 2016), and culture results (Cameron et al., 2013, Cameron et al., 2014, Vasquez et al., 2018) have been common methods in the selection of cows to receive IMMA at dry off. Culturing milk has been considered to be the gold standard for determining IMI (Oliver et al., 2004), but this can be time-consuming and costly. Torres et al. (2008) completed an analysis to determine which selection criteria, based on SCC and CM history would result in the most efficient and accurate selection of cows with an IMI. Results suggest treating cows with a SCC greater than 200,000 cells/mL or cows that had CM after 90 DIM would be most efficient. Authors chose 90 days as a cut in DCT selection because they assumed a case of CM within the first 90 days may be associated with the previous dry period or peak milk production. Results by Cameron et al. (2013, 2014) suggest that farmers may be missing cows with IMI by using only SCC as selection criteria.

According to the meta-analysis completed by Halasa et al. (2009b), SDCT leads to greater success than no treatment at all. Selective therapy led to an overall cure rate of 83% compared to 52% for those not using DCT (Halasa et al., 2009b). When comparing BDCT to SDCT (California Mastitis Test of 2+), Rindsig et al. (1978) concluded that there was little difference between cure rates, with 85.4% and 88.2% of quarter curing over the dry period treated with BDCT and SDCT, respectively. In a more recent study, Cameron et al. (2014) observed no difference in cure rates at a quarter level, 84.5% and 89.0% for BDCT and SDCT (culture positive), respectively.

Like data presented for cure rates, the risk of new IMI has been similar between BDCT and SDCT in some published literature. Halasa et al. (2009c) suggested BDCT offered more protection than when SDCT was carried out at the quarter level rather than the cow level. Treating at the cow level may be more protective because when treating only quarters with an IMI, producers may miss other quarters of the cows that may have a high SCC. When examined at a cow level no differences in new IMI between BDCT and SDCT were reported (Halasa et al., 2009c). Cameron et al. (2014) reported no differences in the risk of new IMI between BDCT and SDCT. Though Cameron et al. (2014) agree with the meta-analysis presented by Halasa et al. (2009c), they suggest selection criteria is important in the success of SDCT.

Scherpenzeel et al. (2016) determined selection criteria also had an impact on the success of SDCT. Herd-level increase in CM ranged from 11.6 when BDCT was used to 14.5 cases per 10,000 cow days when primiparous cows with a SCC > 150,000 and multiparous cows > 250,000 cows were treated. When all cows with a SCC > 50,000 cells/mL were treated, the lowest increase in CM occurred, with 11.8 cases per 10,000 cow days. When examining SCM, BDCT resulted in 38.8% of the herd having a SCC > 200,000 cells/mL. Greater than 48% of cows had a SCC > 200,000 cells/mL. This rate occurred when primiparous cows with a SCC > 150,000 and multiparous cows > 250,000 cows were treated for a total of 47.9% of cows receiving antibiotics at dry off.

Teat Sealants. Teat sealants **(TS)** are applied or infused directly in the teat cistern after the last milking of the cow's lactation. Sealants can be used in conjunction with IMMA or alone in a SDCT scheme. When used with IMMA, TS are administered after the IMMA. In a meta-analysis by Rabiee and Lean (2013), the use of a TS reduced the number of IMI by 25% and 73% compared to cows treated with just IMMA or no treatment, respectively. Teat sealants also reduced the CM at calving by 29% when used alone and 48% when used with an IMMA. Subsequent research also showed a decrease in IMI when using TS (Golder et al., 2016, McParland et al., 2019).

Antibiotic Use. Many countries such as those in the European Union, Scandinavia, and New Zealand now require the use of SDCT (Lam et al., 2017, McDougall, 2018) with hopes that SDCT will reduce the use of antibiotics. Scherpenzeel et al. (2016) compared the total antibiotic use of BDCT and SDCT using different SDCT selection criteria in a stochastic model based on Dutch dairy farm data. The use of antibiotics was based on an average daily dose **(ADD)** per CM case. Scherpenzeel et al. (2016) found that the use of SDCT led to a maximum reduction in antimicrobial use of 40%. Scherpenzeel et al. (2016) concluded that none of the SDCT scenarios led to an additional treatment that exceeded the total IMMA used with BDCT.

Economics of Dry Cow Therapy

In the U.S., surveyed producers spent $15.67 and $12.60 (2019 US$) per cow at dry off for IMMA plus TS and IMMA alone, respectively (USDA Animal and Plant Health Inspection Service, 2016). When calculating the total cost of DCT, not only do treatment expenses (drugs and labor) need to be considered, but also the cost of CM and SCM associated with cases in the dry period need to be included (Huijps and Hogeveen, 2007, Scherpenzeel et al., 2016, Scherpenzeel et al., 2018). In Dutch dairy farms, expenses ranged from (all in 2019 US$) $14.51 to $36.41 per cow for BDCT (IMMA only), $6.40 to $40.23 per cow for SDCT, and $5.58 to $57.55 cow when no DCT was used (Huijps and Hogeveen, 2007). The cost of CM makes up the majority of the total cost of DCT (59%) at $26.37/cow when BDCT was used. Clinical mastitis made up 82% of the total cost of DCT, at $30.43/cow, of the total cost when intramammary antibiotics were not used (Huijps and Hogeveen, 2007). Scherpenzeel et al. (2016) presented similar results, that even though BDCT had the highest total cost, it reduced the overall cost of CM and SCM to the farm. These results suggest that when fewer cows are treated at dry off, the more the cost of mastitis will impact the farm. Scherpenzeel et al. (2016) concluded there comes a point when the cost of mastitis will outweigh the savings from not treating cows.

Scherpenzeel et al. (2018) completed an additional economic analysis using optimization modeling to analyze the benefit of SDCT. The model allowed for the treatment of 0% to 100% of the herd. Overall, economic benefit depended greatly on CM incidence and herd SCC. Blanket dry cow therapy was never optimal compared to SDCT, and no DCT was only optimal compared to BDCT when CM incidence was low.

However, when CM rates and herd SCC were high, treating more cows lowered the total cost of DCT, with a range of $67.54/cow per yr when 85% of cows received treatment to $73.94 with no DCT (2019 US$).

MILK PRICING IN THE UNITED STATES

The US dairy market is made up of different Federal Milk Marketing Orders **(FMMO).** The goal of the FMMO system is to provide order to the marketing of fluid milk between the processor or buyer and the dairy producer. Through the FMMO, the government defines pricing rules that move milk between the farmer, the processor, and the consumer. With the FMMO come three main regulations: 1) minimum prices are set, meaning market conditions can allow processors to pay higher prices, but they cannot pay below the minimum, 2) fluid grade (Grade A) milk is regulated at the farm level, and 3) the processors are regulated where prices are set at the milk plant where the milk is processed, not at the farm.

Within each of the FMMO, the pricing system is based on how the milk within that order is used. The use of milk is broken down into four classes: Class I is used for fluid milk; Class II is used for soft dairy products such as ice cream or yogurt; Class III is used for hard cheeses, and Class IV is used for powdered dairy products (Bailey and Tozer, 2001). The minimum prices are based on a blended price or the weighted average from the four classes based on usage in each of the FMMO.

As a part of the Federal Agriculture Improvement and Reform Act of 1996, dairy pricing for FMMO in the US went through several changes (Bailey and Tozer, 2001). One change was the structure of FMMO themselves. Federal milk marketing orders were reduced from 31 to 11 (Figure 1.2). By reducing the number of FMMO, pricing would be more consistent across larger regions of the US.

As of January 1, 2000, multiple component price **(MCP)** took the place of the Basic Price Formula in setting milk prices. In the Basic Pricing Formula, milk fat was the only component considered, and the value of milk was adjusted based on fat content of 3.5%. Multiple component pricing determined a value for milk fat, protein, and other solids yields. Producer Price Differential **(PPD)** is an additional variable in the MCP formula to account for the value of all the milk received in the FMMO minus the cost to manufacture it, or the uniform price minus the Class III milk price. Uniform price represents the sum of the value of milk used across all four milk classes within the FMMO. The primary objective of MCP is to reflect the value of products made from the milk.

After the consolidation of the FMMO, 6 of the 11 FMMO use MCP to price milk. Marketing orders using MCP include the Pacific Northwest, Upper Midwest, Northeast, Central, Mideast, and Southwest (Figure 1.2). For these six FMMO the milk price paid to the farmer is calculated using the following equation (Congressional Research Service, 2017).

$$MCP = (F * F\$) + (P * P\$) + (O * O\$(+((\frac{MY}{100}) * PPD)$$

Where:

MVMCP = Value of milk using MCP pricing scheme

F = Pounds of fat shipped

F$ = Price per pound of fat

P = Pounds of protein shipped

P$ = Price per pound of protein

O = Pounds of other solids shipped

O$ = Price per pound of other solids

MY = Total milk yield shipped by a herd

PPD = Producer price differential

Cragle et al. (1986) completed an analysis to determine if farmers would be paid more if prices were adjusted for fat and protein rather than fat alone like in the Basic Price Formula. Cragle et al. (1986) concluded that paying farmers based on fat and protein, rather than fat alone, could net the farmer an additional $0.07/cwt of milk. More recently, Bailey et al. (2005) examined the effect of breed on farm income using the MCP scheme in the Mideast FMMO. Bailey et al. (2005) determined that, though Jerseys produce higher component milk, the volume of milk produced by Holsteins made them more profitable. By increasing the components produced by one standard deviation (0.37% fat and 0.15% protein for Holsteins and 0.50% fat and 0.23% protein for Jerseys), farms could increase their income over feed costs by 7.7% and 9.2% for Holsteins and Jerseys, respectively. However, an increase in the total volume would have a greater impact on income over feed cost (Bailey et al., 2005).

Four of the 11 FMMO, including Arizona, Southeast, Florida, and Appalachia price milk using a skim milk and butterfat pricing scheme. In this pricing scheme, dairy farmers are paid based on total pounds of milk and butterfat shipped. Prices of skim milk and fat in these FMMO are calculated with classified formulas. For this reason, members of the dairy industry believe MCP allows for more transparency to farmers in how their milk is priced (Bailey and Tozer, 2001). Because MCP values milk on its end use, dairy farmers can estimate market changes by observing retail and wholesale milk commodity prices.

Though later retracted due fluctuations in the market, in Spring of 2018 National-Jersey Inc., with support of 14 milk cooperatives, sent a proposal to the US Department of Agriculture – Agriculture Marketing Service to change milk pricing in the Appalachia and Southeast FMMO to a MCP scheme (USDA Agricultural Marketing Service, 2018b). Two additional proposals, one supporting the change to MCP (USDA Agricultural Marketing Service, 2018a) and one refuting (USDA Agricultural Marketing Service, 2018c), both discuss how the change to MCP would change milk transportation, handling, and pooling but do not discuss how this change would affect the farm-gate prices to dairy farmers in the Appalachia and Southeast FMMO.

In an analysis of how MCP might impact the Southeastern US, Newton (2014) states that the value of milk produced from 2006 to 2013 would have increased by $25 million and $44 million for Appalachia and Southeast FMMO, respectively. However, the value of milk in the Florida FMMO would have decreased by $1 million. Newton (2014) does warn that these values may not all come back to the dairy producer as they do not account for how processors might adjust to the pricing change. More research is needed to determine how a pricing change to MCP would directly affect farmers in the Southeast.

SUMMARY

Milk quality management is becoming increasingly important as pressure is being put on dairy farmers for lower SCC (Nickerson, 2012, Nolan, 2018) and less antibiotic use (Croney et al., 2012). Somatic cell count remains the gold standard in evaluating milk quality and udder health status at a herd level. Research has shown a relationship between herd SCC and management practice adoption. Though BDCT is still a recommended milk quality management practice in the US, dairy producers may soon be forced to adopt SDCT. Most of the research determining the economics of milk quality management has been modeled under a Dutch dairy system where herd sizes are smaller and producers are no longer allowed to use BDCT. Little to no research had been completed modeling a US dairy herd.

The following dissertation has three objectives. The first is to determine the cost of herd SCC and how costs change after management practices have been implemented to control SCC in a modeled herd. Next, the second objective is to determine if SDCT is more economical compared to BDCT by varying SDCT selection criteria in stochastic simulation models. Finally, the third objective is to provide insight into the potential differences in farm gate milk checks when milk is priced under different pricing schemes.

Figure 1.1. The total economic impact from disease when including both losses and expenditures, also known as the Loss-Expenditure Frontier (McInerney et al., 1992).

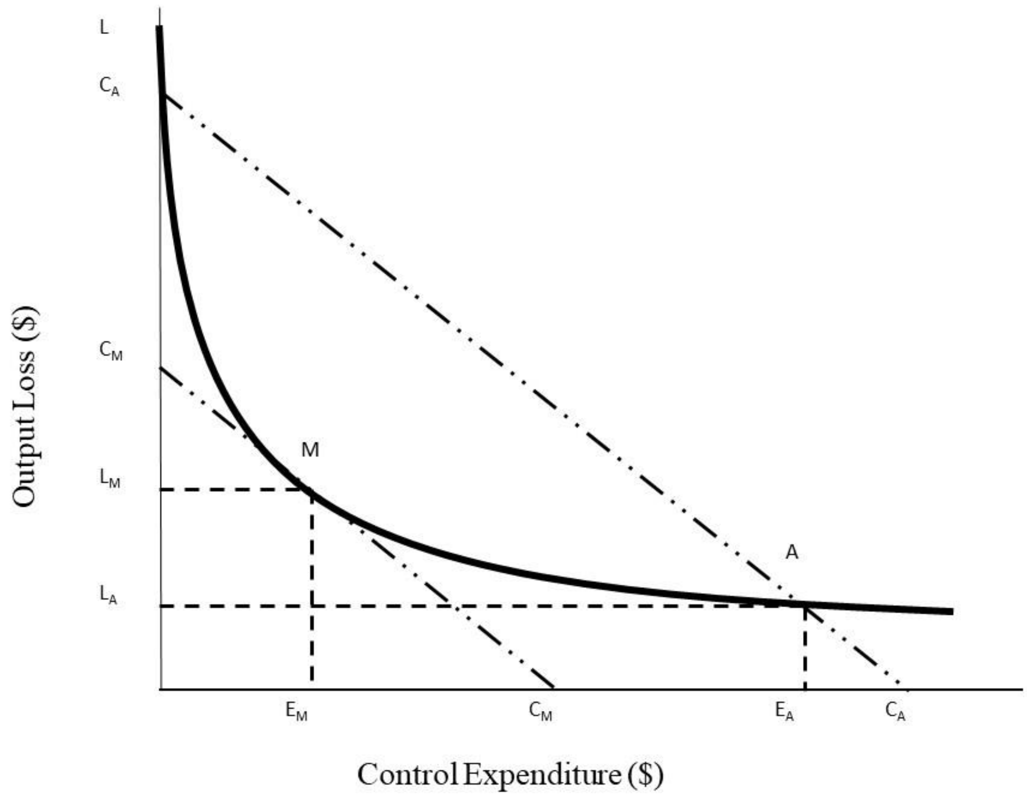
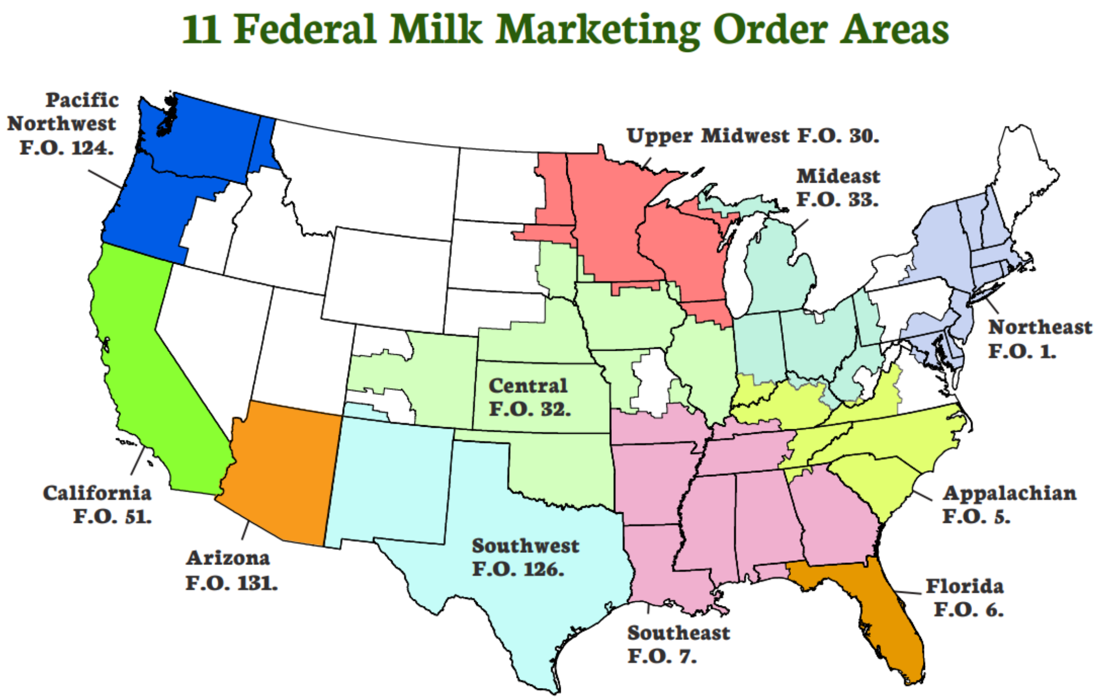


Figure 1.2. Federal Milk Marketing Orders in the United States (USDA Agriculture Marketing Service, 2019a).



2) CHAPTER TWO

The economic effects of management practice adoption on decreasing bulk tank somatic cell counts in simulated United States dairy herds

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INTRODUCTION

Milk somatic cells are composed of epithelial cells and leukocytes. No matter the infection status of the mammary gland of a dairy cow, somatic cells are present in milk. However, when the mammary gland becomes infected with microorganisms, most commonly bacteria (Bradley, 2002), the number of leukocytes and thus somatic cells in milk increases (Schalm et al., 1964, Schalm et al., 1966, Schalm and Ziv-Silberman, 1968, Schukken et al., 2003). Somatic cell count **(SCC)** is a measurement used in the dairy industry to determine the infection status of the mammary gland (Prescott and Breed, 1910, Miller et al., 1993).

Natzke et al. (1972) were one of the first to determine the differences between SCC of milk from cows with and without an intramammary infection and concluded that the average SCC of a healthy mammary gland was 200,000 cells/mL. A SCC of under 200,000 cells/mL is still considered a non-infected mammary gland (Dohoo and Leslie, 1991, Pantoja et al., 2009b, Jadhav et al., 2018). Even though a SCC threshold of 200,000 cells/mL has been used to determine an intramammary infection, milk loss is associated with SCC levels lower than 200,000 cells/mL (Dürr et al., 2008, Hand et al., 2012, Gonçalves et al., 2018, Hadrich et al., 2018)

At a bulk tank or herd level, the legal SCC in the United States is 750,000 cells/mL (U.S. Food and Drug Administration, 2017). However, dairy processors are now determining SCC thresholds for their producers. To export milk products to the European Union, the 3-month rolling average SCC of milk must be < 400,000 cells/mL (Norman et al., 2011, USDA Agricultural Marketing Service, 2013). For this reason, many processors have set their SCC threshold at 400,000 cells/mL. This threshold continues to decrease, with some processors demanding farms have a bulk tank SCC under 250,000 cells/mL (Nickerson, 2012, Nolan, 2018).

Little research has been conducted on the direct effect of management practice implementation on the change of bulk tank SCC. However, multiple studies have examined the difference in management practice adoption between herds with differing SCC (Dufour et al., 2011). In a review study, Dufour et al. (2011) concluded that many different management practices, such as teat disinfectants and blanket dry cow therapy, are implemented by farms with a low SCC (< 250,000 cells/mL). Farm characteristics, such as housing design, bedding material, and milking equipment were also associated with herd SCC (Dufour et al., 2011).

Often the lack of adoption of management practices is due to cost (Jansen et al., 2010). When profit margins in the dairy industry begin to decrease, producers look for new ways to cut costs, and some management practices may be dropped from protocols. However, dairy producers must look at more than just the cost of the practice when making decisions. They must determine the overall current and future economic impact of management practices.

The economic impact of management practices that prevent or cure diseases can be calculated by determining the practice's effect on the total cost of the disease to a herd. Disease costs are composed of expenses and losses of potential income (McInerney et al., 1992). The costs of teat disinfection, dry cow therapy, and labor to control bulk tank SCC are expenses. Losses are the economic impacts that might not be readily apparent to producers e.g., milk production loss, loss of potential premiums.

Total costs associated with disease control strategies can be examined and, in a loss-expenditure analysis (McInerney et al., 1992), used to determine which strategies are the most economically optimal. The economic optimum is the point in which a dollar spent on management practices (expenses) returns exactly a dollar in decreased losses. Besides McInerney et al. (1992), the use of the loss-expenditure method to determine the economic impact of milk quality has been limited. Stott et al. (2002) used a similar method to determine the total cost of *Staphylococcus aureus* mastitis management, while Scherpenzeel et al. (2018) evaluated the effects of dry cow therapy on the cost of clinical mastitis to dairy farms.

Another common modeling approach in dairy research has been stochastic simulation. Stochastic simulation allows researchers to simulate real events and account for variation in inputs used in the model. This modeling technique has been widely used by dairy researchers to estimate the costs of disease (Halasa et al., 2009a, Liang et al., 2017, Dolecheck et al., 2019). However, little research has been done using these economic modeling approaches to determine the economic effect of an elevated herd SCC.

In our study, we combined the loss-expenditure analysis method with stochastic simulation in creating a model to determine how the cost of a herd SCC can be decreased through the adoption of new management practices. Primary objectives of the study were 1) to determine the economic losses associated with an elevated bulk tank SCC, 2) to determine the total cost of a herd's new SCC after the adoption of different cost management practices, and 3) to determine the cost change of decreasing an elevated bulk tank SCC associated with adoption of management practices. Secondary objectives of the study were 1) to determine the change in SCC necessary for the implementation of management practices to be economically feasible and 2) to determine the impact of milk quality premium pricing on the economics of management practice adoption.

MATERIALS AND METHODS

Model Overview

A farm-level simulation model was developed with deterministic and stochastic components. The deterministic component was developed using Excel 2013 (Microsoft, Seattle, Washington) and was first developed by Bewley et al. (2010) with additions by Dolecheck et al. (2016) and Liang et al. (2017). Our model was updated to model three different Holstein herds using Dairy Records Management Systems **(DRMS)** (Dairy Records Management Systems, Raleigh, NC) data. When collecting data from the DRMS database, limit options for “breed” to only include Holstein and no limit options for “state” or “region” were used. The DRMS report was run on November 2, 2018, and collected records from every Holstein herd in the United States that was enrolled in the DRMS program. Results from the DRMS report indicated that the average US Holstein herd processed through DRMS consisted of 205 milking cows with an average lactation yield of 10,336 kg and a SCC of 251,000 cells/mL. These data were used to represent an average SCC herd in our analysis (Farm B). The analysis also included two additional herds within one standard deviation of the average herd’s SCC. The below-average herd (Farm A) had a SCC of 109,000 cells/mL, and the above-average herd (Farm C) had a SCC of 393,000 cells/mL. Herd size and rolling herd average were kept constant between the three herds.

The second component of the model used stochastic variables to simulate the total cost of herd SCC based on the effect of management practice implementation and their changes in the herd SCC. Stochastic variables were created and simulations were done using the Excel add-in, @Risk (Palisade Corporation, Ithaca, NY). Stochastic variables included milk price, management practice costs, resulting change in herd SCC, and milk yield loss associated with an elevated SCC. Using historical milk price variation, predicted milk prices were estimated using the same process described by Bewley et al. (2010) and Liang et al. (2017) to create a stochastic milk price. Historic milk prices were collected over a 10-year period from Gould and Bozic (2018). Milk prices used in the model ranged from \$0.31 to \$0.51/kg of milk with an average of \$0.42/kg of milk. The total cost of the bulk tank SCC was calculated by summing the losses associated with an elevated SCC and the expenses of new management practice adoption.

Losses

Losses from an elevated SCC were derived from potential unrealized milk production or losses associated with a SCC and loss of milk quality premiums. To determine the milk yield losses associated with SCC, results from Hand et al. (2012) were applied based on each herd's bulk tank SCC and multiplied by herd size. Parity distribution of the herd was adopted from Dhuyvetter et al. (2007) to account for a parity effect in milk yield losses where 36.1%, 26.0%, and 37.9% of cows were in parities 1, 2, and 3+, respectively, in a simulated herd of 205 lactating cows. Overall milk yield loss was calculated using the following equation:

$$ML = (0.361 * 205 * PL1) + (0.260 * 205 * PL2) + (0.379 * 205 * PL3)$$

Where:

ML = Total milk yield loss (kg/farm)

PL1 = Milk yield loss (kg/cow) for parity 1 cows based on the SCC threshold of each farm.

PL2 = Milk yield loss (kg/cow) for parity 2 cows based on the SCC threshold of each farm.

PL3 = Milk yield loss (kg/cow) for parity 3 and greater cows based on the SCC threshold of each farm.

Milk quality premiums were calculated using $0.0055 per kg of milk per change in SCC premium level (Table 2.1). To avoid inflation of losses associated with a premium for Farms B and C, it was assumed that they were only losing benefit from one bonus level, rather than the addition of all bonus levels, for a premium loss of $0.0055 per kg of milk produced. If the herd SCC decreased below a premium level or if no premiums were offered, authors assumed no losses were associated with lost premiums. Therefore, total losses were calculated using the following two equations where equation "A" was used when premiums levels were not met and "B" was used when premiums were met or when premiums were not offered.

A) $TL = (ML * 205 * SMP) + (0.0055 * HMY)$

B) $TL = (ML * 205 * SMP)$

Where:

TL = Total losses per farm ($/farm per year)

ML = Milk loss (kg per cow) associated with the bulk tank SCC

SMP = Stochastic milk price ($/kg)

HMY = Herd milk yield (kg/yr) before management practice adoption

Management Expenses

Three different management practices were analyzed based on the cost of implementation (Nolan, 2017). Costs of each management practice were fit with a PERT distribution using the range presented by Nolan (2017) to make the variable stochastic. Management practices were defined as low, moderate, and high expense practices based on the most likely cost and variation in cost of each practice (Table 2.2). Though the management practices were generalized based on expense, the costs of implementation were derived from common management practices used in the dairy industry to control mastitis and improve milk quality. Costs of management practices were calculated on a per cow per year basis and multiplied by the herd size to obtain the total cost of the management practice for the herd.

Change in Somatic Cell Count

Because one of the primary objectives of the study was to determine the change in the total cost of a bulk tank SCC before and after management practice adoption, change in SCC was assumed to be constant across the three management practices analyzed. Keeping the change in SCC consistent between management practices ensured that the only difference between each management practice was the cost of adoption. However, SCC change was specific for each of the three farms based on the original herd SCC of each farm. Values for the change in SCC were fit to a PERT distribution to make the variable stochastic (Table 2.3). By making the change in SCC a stochastic variable, authors were able to calculate a breakeven SCC where the economic benefits of management adoption were no longer feasible. Little data exists showing the cause and effect relationships between the management practice adoption on herd SCC. Therefore, authors estimated changes in SCC that would result in both positive and negative economic benefits of management practice adoption. Estimated changes included a wide distribution to satisfy the secondary objective of the study in determining the change in SCC necessary to make management practice adoption feasible. The herds' SCC after the implementation of the management practice was calculated by taking the difference between the original bulk tank SCC and the change in SCC.

Benefits

Benefits from a lower SCC came in the form of increased milk production and potential milk quality premiums. Estimating milk production increases were achieved by taking the differences in milk yield between SCC thresholds presented by Hand et al. (2012). Results from Hand et al. (2012) were adapted to show the difference in milk yield with one SCC unit (1 cell/mL) change by taking the average of losses (kg/cow per year) from each SCC group of 100,000 cells/mL and dividing by 100,000. For example the losses associated with a SCC between 100,000 cells/mL and 200,000 cells/mL were subtracted from the losses between 200,000 cells/mL and 300,000 cells/mL and divided by 100,000. Results from the calculation were then used to estimate the increase in milk yield per 1 cell/mL associated with a farm decreased from one SCC group to another. A table showing the losses presented by Hand et al. (2012) is located in the appendix (Table A.1).

Premiums were calculated by taking the new bulk tank SCC and determining the correct milk quality bonus. Once the correct bonus level was determined, the associated price was multiplied by the total herd milk yield. The total benefit of management practice adoption was calculated using the following equation.

$$TB = \left((CSCC * MI * SMP * HS) + (PL * 0.0055 * HMY)\right) - ME$$

Where:

TB = Total benefit ($/farm per year)

CSCC = Change in herd SCC (cells/mL)

MI = Milk yield increase (kg/cow per year) associated with the change in SCC

SMP = Stochastic milk price ($/kg)

HS = Lactating herd size

PL = Number of premium levels changed due to change in SCC

HMY = Herd milk yield (kg/year)

ME = Management expenses ($/farm per year)

Change in Cost

To accomplish objective 3, the total cost, including expenses and losses, described by McInerney et al. (1992) was calculated based on the farm's new SCC. The total cost change was calculated using the following equation.

$$CC = TL - (TLN + ME)$$

Where:

CC = Cost change ($/farm per year)

TL = Total economic losses ($/farm per year) associated with the base SCC

TLN = Total economic losses ($/farm per year) associated with the new SCC (calculated as TL - TB)

ME = Management expenses ($/farm per year)

Simulation

A single 1,000-iteration simulation was run collecting output variables including change in bulk tank SCC, total losses associated with the base SCC for each of the three farms, total cost (losses and expenses) associated with the new SCC, and the total cost change with management practice adoption. The simulation was run using Latin Hypercube sampling with a static seed of 31,517 (Liang, 2013, Nolan, 2017, Dolecheck, 2018).

Upon completion of the simulation, each iteration was analyzed across the three farms and management practice costs. Iterations were analyzed to determine the frequency of a positive benefit for each of the three management practices and compared across Farms A (109,000 cells/mL), B (251,000 cells/mL), and C (393,000 cells/mL). The total cost of the new SCC and the change in cost were also analyzed on a per iteration basis. All iterations regarding the cost-benefit analysis of the three management practices and the total cost of the new SCC were further analyzed to complete a mean-variance analysis to complete an economic risk analysis associated with the implementation of the three management practices.

Statistical Analysis

Results from the simulation for the total cost of the herd SCC were analyzed for significant differences before management practice adoption and across all three management practices for all farms. Analyses were completed using Microsoft Excel Simetar (Simetar, College Station, TX) add-in. The means of the cost of SCC associated with each management practice were compared to one another, by farm, using a two-sample T-test to determine significant differences at $P < 0.05$.

Mean-Variance Analysis

After the simulation was run, the mean and variance of the total cost of the new SCC were collected across all farms and management practices. For each management practice, the means were evaluated for the lowest total cost of the new SCC. The variance for the total cost of the new SCC was evaluated for the lowest variance. The combination of the lowest means and lowest variance was assumed to be the least risky management strategy.

Sensitivity Analysis

To satisfy the secondary objectives of the study, a sensitivity analysis was completed by examining the relationship between the change in SCC of all farms and the change in the cost of SCC after the adoption of the high-cost management practice. The high-expense management practice was used because it not only had the highest most likely cost but also had the most variation in cost. Because of the variation in cost, authors were able to determine at what cost a management practice would no longer be feasible to adopt.

Authors felt it was important to include the secondary objective of determining the impact of milk quality premium pricing on the economics of management practice adoption because of current trends in the United States dairy industry. Many milk buyers and processors are no longer offering milk quality premiums, so a single simulation was run with all premiums levels set to $0.00/kg of milk.

RESULTS

After the adoption of any management practice, herd SCC decreased from the base SCC for 98.8%, 99.7%, and 99.8% of the 1,000 simulated iterations for Farms A, B, and C, respectively. Though herd SCC decreased from the base, each herd's new SCC still had associated economic losses because of the continued reduced milk production and potential premium losses associated with the farms' new SCC. Because the change in SCC was assumed to be the same across the different management practices, losses were only specific by farm. Farms reached the next premium level in 91.9%, 61.0% and 21.4% of the 1,000 iterations for Farms A, B, and C, respectively. Not reaching the next premium level resulted in a yearly loss of $11,587.83, per farm, due to lost premiums alone.

Total losses before and after management practice adoption were the lowest for Farm A and highest for Farm C. After the implementation of the management practices, losses decreased by $13,463.56, $12,870.18, and $9,276.09 for Farms A, B, and C, respectively (Table 2.4A). Though losses decreased after the adoption of a management practice, they were more variable before the adoption of management practices across all three farms (Figure 2.1A).

Compared to when a premium was offered, the total losses associated with SCC decreased when no premium was offered. The decrease in losses was because the loss in milk production associated with SCC was the only loss considered. Losses decreased by $2,814.54, $5,801.73, and $6,787.34 for Farms A, B, and C, respectively, after the adoption of the management practices (Table 2.4B). Losses were more variable after the adoption of the management practices when premiums were offered versus when they were not (Figure 2.1B). These trends of variability continue when examining the effect of management practice adoption on the total cost of an elevated SCC to dairy herds.

Low-Expense Management Practices

Premium Offered. The total cost of the low-expense management practice averaged \$587.67 ± 222.24 per farm per year. When examining the total cost of the herds' new SCC, costs ranged from \$10,102.94 to \$18,282.88 (Table 2.5A). The low-expense management practice led to the new SCC costing the least to Farm A and most to Farm C when a milk quality premium was being offered (0A). Regardless of farm type, the low-expense management practice significantly ($P < 0.05$) decreased the cost of SCC to the farms after adoption (Table 2.5A).

The total change in the cost of herd SCC from before to after adoption of the low-expense management practice was highest in Farm A and lowest in Farm C (Figure 2.3A). Farm A had a total change in cost of \$12,875.90 when a premium for milk quality was offered (Table 2.6A). When considering the variation in the total cost, at times, all farms had a higher cost associated with SCC after the implementation of the low-expense management practice. When considering the variation in the total cost, less than 7% of iterations resulted in all farms having a higher cost associated with the herd SCC after the implementation of the low expense management practice.

Variation in the cost change between the SCC before and after management practice adoption was strongly related to the change in SCC. Of the 1,000 iterations, 94.2%, 98.9%, and 99.1% of iterations resulted in the new SCC costing less for Farms A, B, and C, respectively. For Farm A, SCC must have decreased by at least 3,979 cells/mL to see a decrease in the cost of the SCC (Figure 2.4). At a change of 9,000 cells/mL a large increase in the change in cost can be seen in Figure 2.4 due to the farm receiving a premium for decreasing the SCC below 100,000 cells/mL. To see a decrease in the cost of SCC after adoption of the low-expense management practice, the SCC must have decreased by 6,310 and 7,672 cells/mL for Farms B and C, respectively. Like in Farm A, a large increase in the change in the cost of SCC after adoption of the low-expense management practice is observed when each farm reaches the next premium level (Figures 2.6 and 2.8).

No Premium Offered. The total cost of SCC to the farm after adoption of the low-expense management practice ranged from $11,391.22 per year for Farm A to $15,374.69 per year for Farm C when premiums were not offered to the farms (Table 2.5B). The cost of SCC to the farm after adoption of the low-expense management practice were significantly ($P < 0.05$) less than the cost before adoption. Unlike when premiums were offered, Farm C saw the greatest benefit from adoption of the low-expense management practice (Figure 2.3B). The average change in the cost of SCC to Farm C after adoption of the low-expense management practice was $6,199.68 per year (Table 2.6B).

When premiums for milk quality are not offered, the same relationship between the farms' change in SCC and the change in cost are observed. However, the large increase once the farm dropped below the next premium SCC threshold is no longer present (Figures 2.5, 2.7, and 2.9). The lowest change in SCC observed for Farms A, B, and C in which the cost in SCC decreased after adoption of the management practice was a decrease of 3,979, 6,310, and 7,672 cells/mL respectively. However, farms needed to have a decrease in SCC of approximately 10,000 cells/mL before all iterations resulted in the positive economic benefit to the farm.

Moderate-Expense Management Practices

Premium Offered. Cost of implementation of the moderate-expense management practice averaged \$2,490.40 ± 378.30 per farm per year. The total cost of the new SCC after the adoption of the moderate-expense management practice ranged from \$12,005.72 per year for Farm A to \$20,185.66 per year for Farm C (Table 2.5A). Though the cost was lowest for Farm A (Figure 2.2A), the adoption of the moderate-expense management practices significantly ($P < 0.05$) lowered the cost of SCC to each farm (Table 2.5A).

Adopting the moderate-expense management practice was the most beneficial for Farm A. The average change in cost ranged between \$6,776.65 for Farm C to \$10,973.12 for Farm A (Table 2.6A). When premiums were offered, 91.9%, 89.7%, and 92.7% of iterations resulted in a positive cost change for Farms A, B, and C, respectively.

To result in a positive cost change after the adoption of a moderate-expense management practice, the SCC must have decreased by 9,013 cells/mL for Farm A, 21,712 cells/mL for Farm B, and 18,923 cells/mL for Farm C. Once each farm reached the next bonus level, the change in cost of SCC increased (Figures 2.4, 2.6, and 2.8).

No Premium Offered. When no premium was offered to the farms, the cost of SCC after adoption of the moderate-expense management practice was highest in Farm C and lowest in Farm B. The cost of SCC after adoption of the moderate-expense management practice was \$9,370.11 per year for Farm B. Across all farms, the cost of SCC significantly ($P < 0.05$) decreased after the adoption of the management practice (Table 2.5B).

The change in cost of SCC after the adoption of the moderate-expense management practice was lowest in Farm A (\$324.10 per year) and highest in Farm C (\$4,296.90) (Figure 2.3). Farms B and C saw a benefit from management practice adoption in 89.7% and 92.7% of iterations, respectively (Figures 2.7 and 2.9). However, unlike when premiums were offered, Farm A saw a decrease in the cost of SCC after adoption of the moderate-expense management practice in 59.3% of iterations (Figure 2.5). The decrease in iterations in which the cost of SCC was lower after management practice adoption suggests that when a premium is provided management practices become more economical.

High-Expense Management Practices

Premium Offered. Average costs of the high-expense management practice were $4,003.60 ± 2,116.91 per farm per year. Based on the implementation of the high-expense management practice, the cost of the new SCC was lowest in Farm A ($13,889.28/farm per year) and highest in Farm C ($21,698.12/farm per year) (Table 2.5A). Across all farms, the cost of SCC significantly ($P < 0.05$) decreased after adoption of the high-expense management practice.

Farm A had the highest change ($9,460.67/farm per year) when premiums were being offered (Table 2.6A) (Figure 2.3A). The frequency of iterations in which the change in cost of SCC was positive was 92.2%, 78.5%, and 77.5% for Farms A, B, and C, respectively (Figures 2.4, 2.6, and 2.8). To have a positive change in the cost of SCC, Farm C needed to have the highest SCC change of at least 10,925 cells/mL. In one iteration, Farms A and B had to decrease their SCC by 6,934 and 6,124 cells/mL, respectively, before the high expense management practice was a positive benefit. When farms reached the SCC threshold to receive a premium, the change in cost of SCC increased dramatically.

Not only did the high-expense management practice cost the farms the most on average, but it also had the most variation in cost. This allowed the authors to determine at what cost a management practice no longer became economically feasible. When premiums are being offered to the farm, Farm C was the only farm limited by the cost of the management practice. Once the costs of the management practices increased above $47.88/cow per year, all total costs changes from lowering the herd SCC were negative for Farm C (Figure 2.10). Farms A and B could spend over $50.00 per cow per year and still see a benefit of lower total SCC costs if they reached the SCC threshold for a premium. If the threshold for the premium was not reached, management expenses as low as $3.38, $7.06, and $3.34 per cow per year resulted in higher total SCC costs than before adoption (Figure 2.10) for Farms A, B and C, respectively.

No Premium Offered. Adoption of the high-expense management practice resulted in a significantly ($P < 0.05$) lower SCC cost for Farms B and C (Table 2.5B). Costs of SCC after adoption of a high-expense management practice ranged from $10,882.57 per year for Farm B to $12,590.24 per year for Farm C. However, Farm C had the greatest change in cost, saving $2,784.44 per year (Table 2.6B). When no premiums were offered, Farm A had a significant ($P < 0.05$) increase in the cost of SCC after adoption of the high-expense management practice (Table 2.5B). Farm A averaged a negative change in cost (-$1,188.36/year) (Figure 2.3B), suggesting that investment in a high-expense management practice will rarely pay off for farms with a lower SCC.

Only 35% of the iterations ran led to a positive cost change for Farm A (Figure 2.5). To ensure a positive change in the cost of SCC, Farm A had to decrease SCC by 6,934 cells/mL (Figure 2.5). In 71.3% and 77.3% of iterations, the cost of SCC decreased for Farms B and C, respectively. To result in a positive change in the cost of SCC, Farm B needed to decrease SCC by 6,124 cells/mL and Farm C needed to decrease by 10,925 cells/mL (Figures 2.7 and 2.9). The maximum farms could spend and still benefit economically from the lower SCC was $26.63, $42.91, and $47.88/cow per year for Farms A, B, and C, respectively (Figure 2.11).

Mean-Variance Analysis

A mean-variance analysis was completed across all management practices to help dairy farmers consider the financial risk of adopting a management practice. When comparing the mean and variance for the effect of each management practice on the total cost of the new SCC, the low-expense management practice had the lowest mean cost and variance across all herd types when farms were offered a premium for milk quality (Table 2.7A). The low-expense management practices also resulted in the lowest cost and variation when premiums were not offered (Table 2.7B). The mean and variance were higher when premiums were offered (Figure 2.12) compared to when they were not (Figure 2.13). As expected, the low-cost management practice having the lowest total SCC cost and least variance suggests that it would be the least risky to implement regardless of whether premiums for milk quality are offered to farms.

DISCUSSION

Most of the economic research focused on milk quality in the dairy industry has focused the cost of clinical mastitis. Little research has addressed costs associated with specific SCC, and the research that has been done is primarily on the losses associated with SCC. One objective of our study was to determine the total cost of herd SCC by considering both milk income losses (lost milk production and premiums) and the expenses of implementing new management practices to decrease SCC.

McInerney et al. (1992) first discussed the total economic impact of disease and completed an analysis determining the total cost of subclinical mastitis. They concluded that subclinical mastitis had the least total economic impact on farmers who implemented all three management practices modeled (teat disinfection, dry cow therapy, and equipment maintenance) because the cost of subclinical mastitis to a farm was lowest when the farm used all three management practices. Costs were lowest to the farm that used all the management practices because their adoption lowered subclinical mastitis incidence. In our analysis, a more general approach was taken. According to USDA Animal and Plant Health Inspection Service (2016), of the farms polled, 85% used a pre-milking teat disinfectant, 97% used a post-milking teat disinfectant, 97% treated clinical mastitis cases, and 93% treat every quarter of every cow at dry-off. No information on the frequency of milking maintenance was reported by USDA Animal and Plant Health Inspection Service (2016). These results suggest that most surveyed dairy farmers in the United States have adopted the original 5-point mastitis plan (Dodd and Neave, 1970) developed by the National Mastitis Council. Because farmers have adopted practices modeled by McInerney et al. (1992) (teat disinfection and dry cow therapy), we decided to examine costs of general management practices rather than examining the adoption of specific management practices. We believe this will allow our research to be relevant through time as more SCC management practices are developed. However, costs were derived from management practices already on the market (USDA Animal and Plant Health Inspection Service, 2016, Nolan, 2017).

In a simulation model, McInerney et al. (1992) concluded that subclinical mastitis had the least economic impact on farms that implemented the use of a teat disinfectant all year, applied dry cow therapy to every quarter of every cow at dry off, and tested and repaired milking equipment annually. Subclinical mastitis cost the farm $4,109.35/farm per year (adjusted to 2019 US$). The farm that was impacted the most by subclinical mastitis only implemented teat disinfection part of the year, did not dry cow treat, and did not perform milking machine maintenance ($9,829.50/farm per year) (2019 US$). The reasons for the increased losses in this herd compared to the losses of a herd that did not adopt any of the practices were due to the increased costs of teat disinfection with no decrease in subclinical mastitis incidence rate because the disinfectant was only used part of the time.

Our model and the model used by McInerney et al. (1992) were similar in the way the cost of decreased milk quality was calculated to include 1) milk loss, 2) loss of milk quality premiums and 3) management practice expenses. In our study, the total costs of the herd SCC seem higher than results presented by McInerney et al. (1992). However, once accounting for inflation, currency conversion, and herd size, results presented by McInerney et al. (1992) fell within the range of our results. McInerney et al. (1992) calculated milk quality costs for a 100-cow herd where ours were calculated for 205 cows. The $9,829.50 cost of subclinical mastitis presented above for a 100-cow herd is equivalent to $20,150.48 for a 205-cow herd, which is within the range of results presented in our study. The range presented in our results is because of the modeling technique. By using stochastic variables we were able to account for ranges of input variables. Differences in results of our study and McInerney et al. (1992) may be due to the assumptions made in each model and modeling technique. Premiums in our model were lower with a $0.0055/kg of milk produced compared to a $0.03/kg (2019 US$) used by McInerney et al. (1992). However, the milk yield per cow per year was much greater in our model (10,336 kg versus 4,900 kg) because we used current milk yield of a US herd whereas McInerney et al. (1992) used milk data from the United Kingdom in 1988.

Hadrich et al. (2018) estimated the total losses associated with a SCC above 100,000 cells/mL using Dairy Herd Improvement data from US herds. Losses from decreased milk yield ranged from $1.20/cow per day to $2.06/cow per day when the cow had a SCC above the 100,000 cell/mL threshold for one month and 10 months, respectively. In our study, milk production economic losses due to an increased SCC were $0.13, $0.16, and $0.20/cow per day for Farms A, B, and C, respectively. One of the main reasons for differences between the results presented by Hadrich et al. (2018) and ours is because we averaged the losses across the whole herd rather than examining the losses at the cow level. When estimating losses at a cow level, Hadrich et al. (2018) compared milk income from cows with varying SCC and other individual cow characteristics and concluded that individual characteristics (e.g. breed, lactation, days in milk, and number of days with a SCC > 100,000 cells/mL) were highly influential of monetary losses. Another difference in loss calculation was that they used milk price data from one point in time, whereas we used prices over a ten-year period in a stochastic simulation.

Additional income from SCC premiums contributed to whether or not the investment in management practices lowered the total cost of SCC in each of the three herds. Dekkers et al. (1996) examined the effect of a $0.02/kg of milk (2019 US $)

penalty for herd SCC above 500,000 cells/mL in three out of four months. Dekkers et al. (1996) concluded that lowering herd SCC led to significant increases in milk revenue with an average profit of $45.72/cow per year (2019 US$) when the SCC decreased by one linear score. Under the pricing scheme in our model, dairy farmers could benefit by $56.52/cow per year by reaching the next premium structure level. The frequency in which premiums were paid was highly dependent on the herds' base SCC and how far the herds base SCC was from a premium level. Producers received a premium on 91.9%, 61.0%, and 21.4% of iterations for Farms A, B, and C, respectively. The decreased percentage of iterations in which Farm C received a milk quality premium was due to the farm's base SCC being 393,000 cells/mL, 93,000 cells/mL away from the next bonus level. Farms A and B were much closer to reaching the next bonus at 9,000 and 51,000 cells/mL, respectively. The frequency of positive iterations in which farms received a premium was the reason cost alleviation was the highest in Farm A. Once the premium was no longer offered, Farm C had the highest cost change. When a premium is offered farmers should consider whether implementation of a new management practice will lower their SCC to the next premium or bonus level. In the farms modeled, the closer the base SCC was to the next bonus level, the greater the average benefit from lowering the herd SCC.

Over the past decade, the thresholds for acceptable milk SCC have been lowered by many processing plants and cooperatives (Norman et al., 2011). Some milk buyers are no longer offering premiums (Nickerson, 2012) for SCC and have either adopted penalties or have eliminated an incentive system altogether. We completed an additional simulation in which premiums for milk quality were no longer offered. When premiums were no longer offered, Farm C had the greatest cost change from the base to the new SCC across all three management practices. These results suggest that farms with a higher SCC, Farms B and C in our model, have the most to gain economically from management practice adoption or other means to reduce SCC. However, for Farm A, the frequency in which the moderate and high-cost management practices were economically beneficial decreased when no premiums were offered. When considering the high-expense management practice, the average change in the cost of SCC was negative. These results suggest that without the increased profit from potential premiums, the adoption of management practices might not be economically feasible for Farm A (low SCC farm).

Not providing a premium to farmers for milk quality may decrease the incentive for dairy farmers to lower their SCC. Valeeva et al. (2007) found that dairy farmers are more likely to take steps to lower their herd SCC when they are penalized for not meeting quality thresholds. When premium incentives are in place, dairy farmers should view the potential income as a reason to improve their milk quality.

By performing a two-sampled T-test analysis, we were able to determine if adoption of management practices would significantly ($P < 0.05$) decrease the cost of herd SCC. Results indicated that regardless of whether premiums were offered, adoption the low-expense management practice resulted in significantly lower SCC costs than all other management practices (Tables 2.5A and 2.5B). Because the cost of SCC was significantly lower, implementation of the low-expense management practice would be the most economically feasible. Results from the mean-variance also indicate adoption of the low-expense management practice would be the least risky option for farmers.

Therefore, when implementing practices to lower herd SCC, farmers should start with low cost management practices first. If the practice does not result in the desired SCC change, less income is lost. Adopting a low cost management practice first becomes more important as SCC premiums become offered less often because the potential income from lowering SCC dramatically decreases when premiums are not offered.

Little research has been done examining the direct effect of management practice implementation on herd SCC. Dufour et al. (2011) completed a review study examining the effect of management practices on herd SCC. However, of the 36 papers analyzed the only papers that presented an examination of herd SCC before and after the implementation of a management practice were evaluating the change from a conventional to an automatic milking system (Klungel et al., 2000, Rasmussen et al., 2001, Rasmussen et al., 2002). Other studies have examined the relationship between the herd SCC and management practices that were already being used by the farm (Barkema et al., 1998a, Wenz et al., 2007, Schewe et al., 2015). Because of the lack of research and our research objectives, we used estimated changes in SCC and PERT distributions.

When building the range or distribution around the stochastic variables used in the model, we chose to use a PERT distribution. The use of a PERT distribution allowed for the building of distributions in which little research has been published. For example, with SCC, we were able to estimate a minimum, most likely, and maximum change in SCC rather than provide a mean and standard deviation to build the distribution.

Within each farm, changes in SCC after implementation of a management practice were kept the same between each management practice to ensure that differences between management practices were from cost alone. However, we assumed that the implementation of the management practices would affect the three herds differently where the higher the base SCC, the more change a management practice would have on the new SCC. Our distributions for the change in SCC resulted in some iterations where the new SCC was higher than the base. We allowed for the increase in SCC above the base to model the occasions in which management practices are not implemented properly. Not implementing a management practice correctly will cost more money to farmers than not adopting the management practice altogether. A secondary objective of our study was to determine the SCC change necessary for the implementation of management practices to become feasible. We felt by including a large range in the change in SCC rather than a specific change, we had a better chance of determining the decrease in SCC necessary for management practices to pay off.

The use of DRMS data as a base herd does not represent average Holstein herd in the US, but rather the average Holstein herd that has data processed through DRMS. Though the use of DRMS records allowed for the simulation of farms using US farm data, only a fraction of farms are enrolled in DRMS. As of 2017, 11,000 (Dairy Records Management Systems, 2017) of the 37,750 (USDA National Agricultural Statistics Service, 2017) (29%) licensed dairy farms in the US were enrolled in DRMS.

We also chose differing herd SCC (low (109,000 cells/mL) and high (393,000 cells/mL)) based on one standard deviation of the average SCC herd (251,000 cells/mL). For these reasons, results from our analysis are not be representative of all dairy herds but rather those with similar characteristics and assumptions as the simulated herds. The fewer cows the farm milks, the more of an effect one or two cows might have on the herd's SCC. When one cow has a large impact on SCC, the most economical decision may be to cull the cow from the herd. The economics of culling have been examined extensively when determining the cost of mastitis (Bar et al., 2008a, Heikkila et al., 2012). However, examining the effect of culling on the economics of herd SCC was beyond the scope of this study.

CONCLUSIONS

Primary objectives of the study were 1) to determine the economic losses associated with an elevated bulk tank SCC, 2) to determine the total cost of a herd's new SCC after the adoption of different cost management practices, and 3) to determine the cost change of decreasing an elevated bulk tank SCC associated with adoption of management practices. Secondary objectives of the study were 1) to determine the change in SCC necessary for the implementation of management practices to be economically feasible and 2) to determine the impact of milk quality premium pricing on the economics of management practice adoption. When adopting management practices, producers should consider the costs compared to the benefits. However, they must also consider the total impact of an elevated SCC to their farm. The results from our simulations of a 205 cow Holstein herd suggest that low cost ($2.65/cow/yr) management practices often pay for themselves by lowering the total cost of an elevated herd SCC. However, moderate ($11.32/cow/yr) and high ($14.60/cow/yr) cost management practices can lead to a higher total cost of an elevated SCC depending on the herds' base SCC. These results also depend on the assumption that each management practice had the same effect on herd SCC. Overall, the cost of SCC significantly decreased after adoption of any of the three management practices. When herd SCC lowered enough to receive a premium, the cost of SCC to the farm was dramatically decreased.

Table 2.1. Bulk tank somatic cell count (SCC) thresholds in which a premium of \$0.0055/kg of milk was offered in a stochastic simulation model to estimate the economic benefit of lowering a herd somatic cell count.

SCC premium level (cells/mL)
SCC < 100,000
100,000 < SCC < 200,000
200,000 < SCC < 300,000
300,000 < SCC < 400,000
400,000 < SCC < 500,000

Table 2.2. Minimum, most likely, and maximum costs ($/cow per yr) for different expense management practices used to create a PERT distribution in a stochastic simulation model to determine the economic benefit of management practice adoption in lowering the herd somatic cell count.

	Distribution of expenses ($/cow per yr)		
Management practice	Min	Most Likely	Max
Low-Expense	$0.40	$2.65	$6.20
Moderate-Expense	$8.65	$11.32	$18.96
High-Expense[1]	$0.37	$14.60	$58.40

[1]High-expense management practice not only had the highest most likely cost but also the largest distribution to determine at what specific cost management practices were no longer economically feasible.

Table 2.3. The estimated distribution of change in herd somatic cell count (SCC) used to create a PERT distribution in a stochastic simulation model to determine the economic benefit of management practice[1] adoption in lowering the herd somatic cell count for three simulated dairy farms.

	Distribution of change in SCC		
Farm	Min	Most likely	Max
Farm A[2]	-10,000	30,000	60,000
Farm B[3]	-10,000	60,000	120,000
Farm C[4]	-10,000	70,000	140,000

[1]Three different management practices were modeled to determine change in SCC cost after adoption of the management practice. Authors assumed that all three management practices would have the same effect on herd SCC.
[2]Farm A base SCC = 109,000 cells/mL
[3]Farm B base SCC = 251,000 cells/mL
[4]Farm C base SCC = 393,000 cells/mL

Table 2.4. Mean (± standard deviation) losses ($/farm per yr) associated with a somatic cell count when three simulated dairy farms are A) offered a milk quality premium[1] and B) not offered a milk quality premium before and after adoption of a management practice.

A)

	Losses before and after management practice adoption ($/farm per yr)		
Farm	Before	After	Change
Farm A[2]	$22,978.84 ± 1,208.31	$9,515.28 ± 4,138.86	$13,463.56
Farm B[3]	$24,269.02 ± 1,345.16	$11,398.84 ± 7,820.47	$12,870.18
Farm C[4]	$26,962.31 ± 1,630.85	$17,695.22 ± 7,118.68	$9,267.09

B)

	Losses before and after management practice adoption ($/farm per yr)		
Farm	Before	After	Change
Farm A[2]	$11,391.22 ± 1,208.31	$8,576.68 ± 1,617.65	$2,814.54
Farm B[3]	$12,681.40 ± 1,345.16	$6,879.67 ± 2,563.78	$5,801.73
Farm C[4]	$15,374.69 ± 1,630.85	$8,587.35 ± 2,982.15	$6,787.34

[1]Premium = $0.0055/kg of milk

[2]Farm A base SCC = 109,000 cells/mL

[3]Farm B base SCC = 251,000 cells/mL

[4]Farm C base SCC = 393,000 cells/mL

Table 2.5. Mean (± standard deviation) total cost ($/farm per yr) of herd SCC before and after adoption of management practices when three simulated dairy farms are A) offered a milk quality premium[1] and B) not offered a milk quality premium.

A)

	Cost of SCC before and after management practice adoption ($/farm per yr)			
Farm	Before[2]	Low[3]	Moderate[4]	High[5]
Farm A[6]	$22,978.84 ± 1,208.31[a]	$10,102.94 ± 4,151.90[b]	$12,005.72 ± 4,172.32[c]	$13,889.28 ± 4,675.42[d]
Farm B[7]	$24,269.02 ± 1,345.16[a]	$11,986.50 ± 7,824.94[b]	$13,889.28 ± 7,829.81[c]	$15,401.74 ± 4,675.42[d]
Farm C[8]	$26,962.31 ± 1,630.85[a]	$18,282.88 ± 7,130.25[b]	$20,185.66 ± 7,138.78[c]	$21,698.12 ± 7,343.70[d]

B)

	Cost of SCC before and after management practice adoption ($/farm per yr)			
Farm	Before[2]	Low[3]	Moderate[4]	High[5]
Farm A[6]	$11,391.22 ± 1,208.31[a]	$9,164.34 ± 1,636.04[b]	$11,067.12 ± 1,680.15[c]	$12,579.58 ± 2,692.95[d]
Farm B[7]	$12,681.40 ± 1,345.16[a]	$7,467.33 ± 2,577.44[b]	$9,370.11 ± 2,592.92[c]	$10,882.57 ± 3,267.01[d]
Farm C[8]	$15,374.69 ± 1,630.85[a]	$9,175.01 ± 2,999.89[b]	$11,077.78± 3,015.49[c]	$12,590.24 ± 3,598.76[d]

[1]Premium = $0.0055/kg of milk
[2]Before = losses associated with SCC before adoption of any management practice
[3]Low cost = Most likely = $2.65/cow/yr with range from $0.40 to $6.20/cow per yr
[4]Moderate cost = Most likely = $11.32/cow/yr with range from $8.65 to 18.96/cow per yr
[5]High cost = Most likely = $14.60/cow/yr with range from $0.37 to $58.40/cow per yr
[6]Farm A base SCC = 109,000 cells/mL
[7]Farm B base SCC = 251,000 cells/mL
[8]Farm C base SCC = 393,000 cells/mL
[a-d] Means within a row with a different superscript are significantly different (*P* < 0.05)

Table 2.6. Mean (± standard deviation) of the change in cost ($/farm per yr) of herd SCC after adoption of management practices when three simulated dairy farms are A) offered a milk quality premium[1] and B) not offered a milk quality premium.

A)

	Change in cost of SCC after management practice adoption ($/farm per yr)		
Farm	Low[2]	Moderate[3]	High[4]
Farm A[5]	$12,875.90 ± 4,053.36	$10,973.12 ± 4,073.69	$9,460.67 ± 4,571.82
Farm B[6]	$12,282.52 ± 7,814.34	$10,379.74 ± 7,818.87	$8,867.28 ± 7,959.04
Farm C[7]	$8,679.43 ± 7,064.43	$6,776.65 ± 7,072.57	$5,264.20 ± 7,265.93

B)

	Change in cost of SCC after management practice adoption ($/farm per yr)		
Farm	Low[2]	Moderate[3]	High[4]
Farm A[5]	$2,226.88 ± 1,361.93	$324.10 ± 1,412.88	-$1,188.36 ± 2,506.12
Farm B[6]	$5,214.07 ± 2,559.09	$3,331.29 ± 2,573.64	$1,798.83 ± 3,226.87
Farm C[7]	$6,199.68 ± 2,923.89	$4,296.90 ± 2,938.77	$2,784.44 ± 3,507.00

[1]Premium = $0.0055/kg of milk
[2]Low cost = Most likely = $2.65/cow/yr with range from $0.40 to $6.20/cow per yr
[3]Moderate cost = Most likely = $11.32/cow/yr with range from $8.65 to 18.96/cow per yr
[4]High cost = Most likely = $14.60/cow/yr with range from $0.37 to $58.40/cow per yr
[5]Farm A base SCC = 109,000 cells/mL
[6]Farm B base SCC = 251,000 cells/mL
[7]Farm C base SCC = 393,000 cells/mL

Table 2.7. The mean and variance of the total cost ($/farm per yr) of herd SCC after adoption of management practices when three simulated dairy farms are A) offered a milk quality premium[1] and B) not offered a milk quality premium.

A)

	Mean of total SCC cost by management practice			Variance of total SCC cost by management practice		
Farm	Low[2]	Moderate[3]	High[4]	Low[2]	Moderate[3]	High[4]
Farm A[5]	$10,102.94	$12,005.72	$13,518.18	17,238,230.00	17,408,280.00	21,859,580.00
Farm B[6]	$11,986.50	$13,889.28	$15,401.74	61,229,710.00	61,305,930.00	63,678,500.00
Farm C[7]	$18,282.88	$20,185.66	$21,698.12	50,840,470.00	50,962,180.00	53,929,900.00

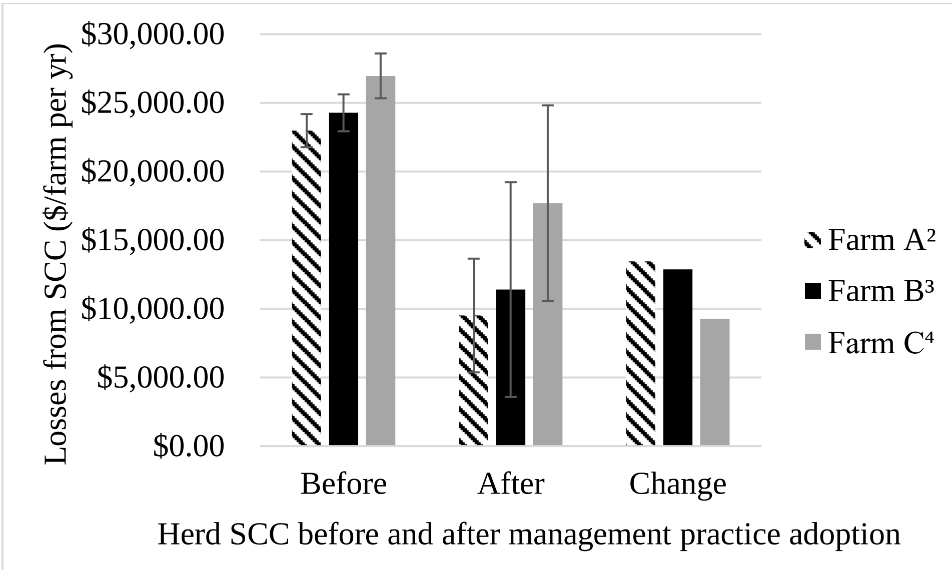
B)

	Mean of total SCC cost by management practice			Variance of total SCC cost by management practice		
Farm	Low[2]	Moderate[3]	High[4]	Low[2]	Moderate[3]	High[4]
Farm A[5]	$9,164.34	$11,067.12	$12,579.58	2,676,643	2,822,888	7,251,957
Farm B[6]	$7,467.33	$9,370.11	$10,882.57	6,643,192	6,723,228	10,673,380
Farm C[7]	$9,175.01	$11,077.78	$12,590.24	8,999,338	9,093,161	12,951,070

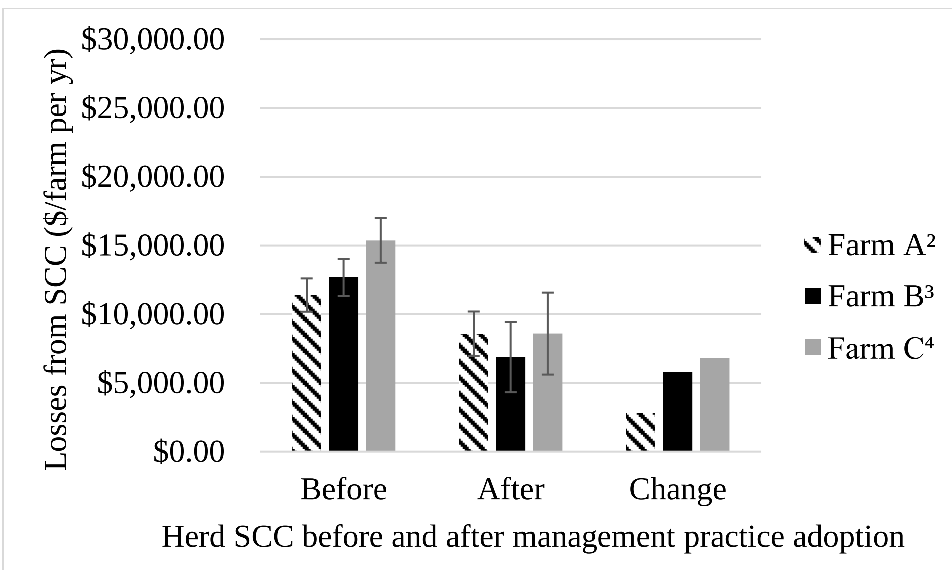
[1]Premium = $0.0055/kg of milk
[2]Low cost = Most likely = $2.65/cow/yr with range from $0.40 to $6.20/cow per yr
[3]Moderate cost = Most likely = $11.32/cow/yr with range from $8.65 to 18.96/cow per yr
[4]High cost = Most likely = $14.60/cow/yr with range from $0.37 to $58.40/cow per yr
[5]Farm A base SCC = 109,000 cells/mL
[6]Farm B base SCC = 251,000 cells/mL
[7]Farm C base SCC = 393,000 cells/mL

Figure 2.1. Mean (± standard deviation) losses ($/farm per yr) associated with an elevated somatic cell count, when three simulated dairy farms are A) offered a milk quality premium[1] and B) not offered a milk quality premium, before and after adoption of a management practice.

A)



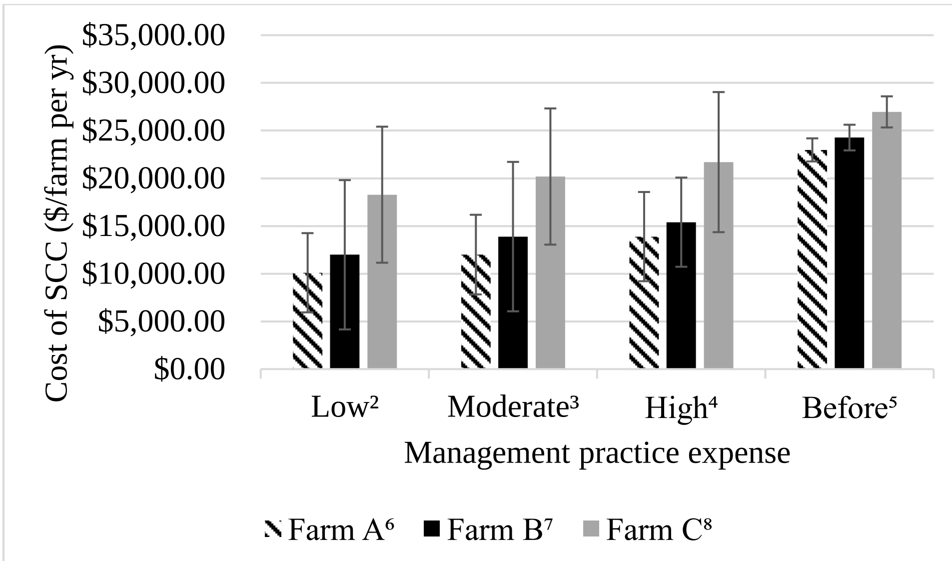
B)



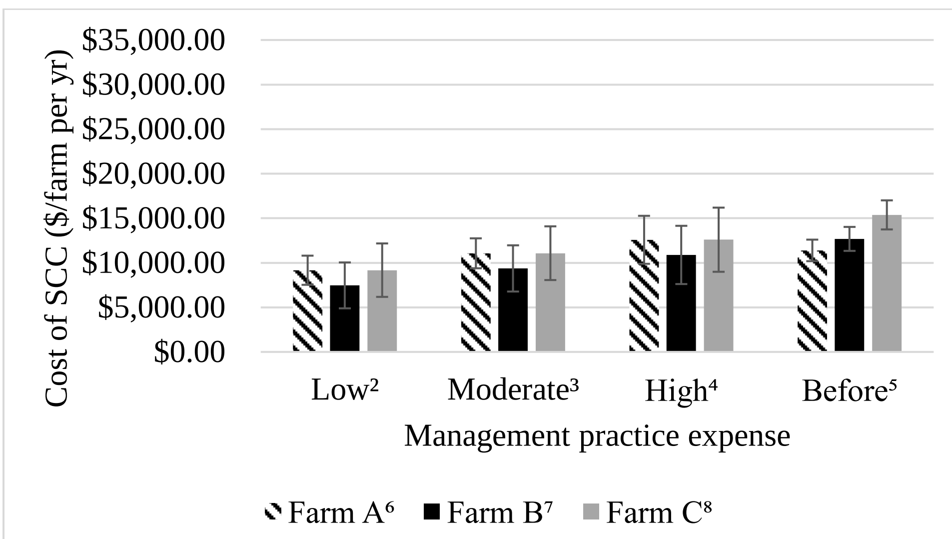
[1]Premium = $0.0055/kg of milk
[2]Farm A base SCC = 109,000 cells/mL
[3]Farm B base SCC = 251,000 cells/mL
[4]Farm C base SCC = 393,000 cells/mL

Figure 2.2. Mean (± standard deviation) total cost ($/farm per yr) of herd somatic cell count (SCC) before and after adoption of management practices when three simulated dairy farms are A) offered a milk quality premium[1] and B) not offered a milk quality premium.

A)



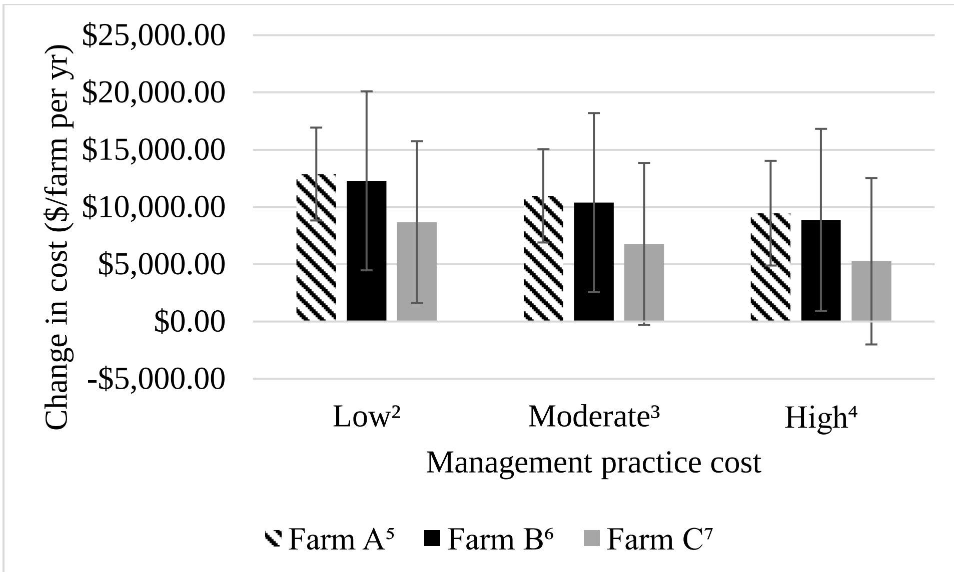
B)



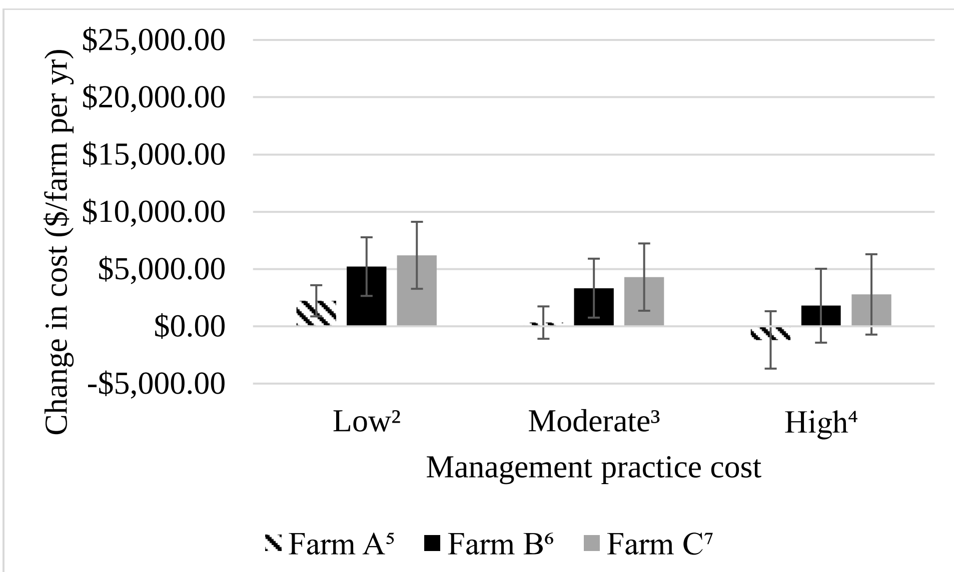
[1]Premium = $0.0055/kg of milk
[2]Low cost = Most likely = $2.65/cow/yr with range from $0.40 to $6.20/cow per yr
[3]Moderate cost = Most likely = $11.32/cow/yr with range from $8.65 to 18.96/cow per yr
[4]High cost = Most likely = $14.60/cow/yr with range from $0.37 to $58.40/cow per yr
[5]Before = losses associated with SCC before adoption of any management practice
[6]Farm A base SCC = 109,000 cells/mL
[7]Farm B base SCC = 251,000 cells/mL
[8]Farm C base SCC = 393,000 cells/mL

Figure 2.3. Mean (± standard deviation) of the change in cost ($/farm per yr) of herd somatic cell count (SCC) after adoption of management practices when three simulated dairy farms are A) offered a milk quality premium[1] and B) not offered a milk quality premium.

A)

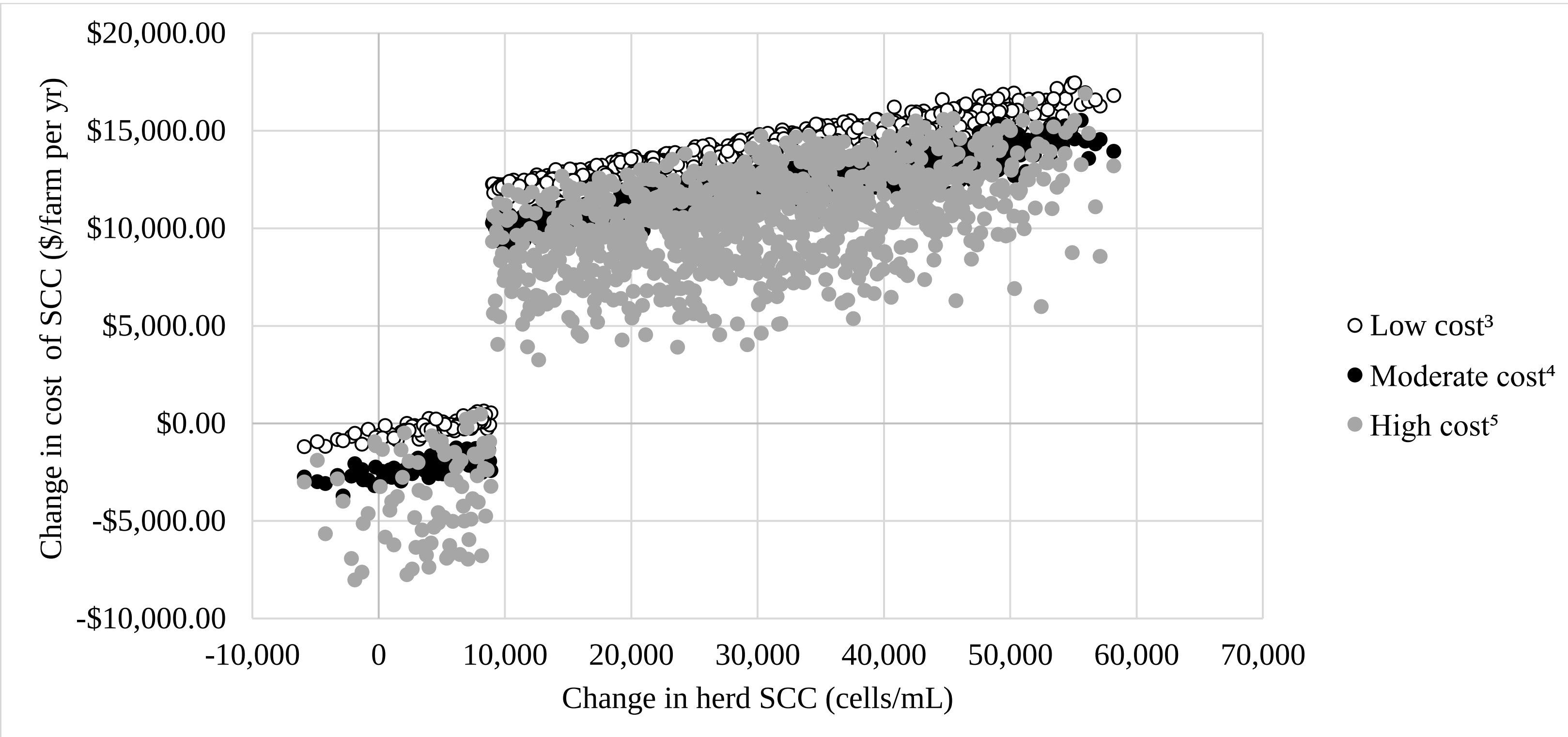


B)



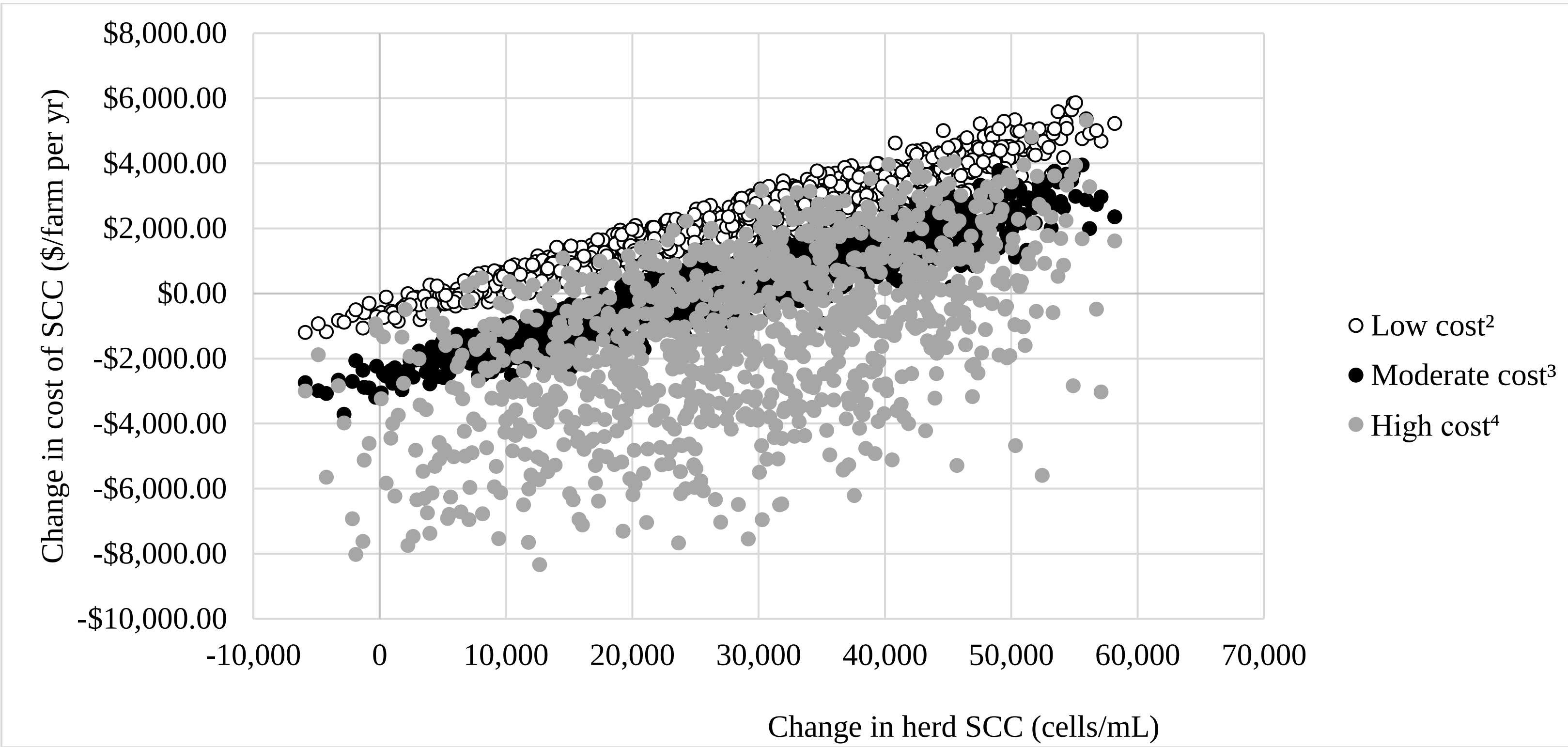
[1]Premium = $0.0055/kg of milk
[2]Low cost = Most likely = $2.65/cow/yr with range from $0.40 to $6.20/cow per yr
[3]Moderate cost = Most likely = $11.32/cow/yr with range from $8.65 to 18.96/cow per yr
[4]High cost = Most likely = $14.60/cow/yr with range from $0.37 to $58.40/cow per yr
[5]Farm A base SCC = 109,000 cells/mL
[6]Farm B base SCC = 251,000 cells/mL
[7]FarmC base SCC = 393,000 cells/mL

Figure 2.4. The change in cost ($/farm per yr) from reducing herd somatic cell count (SCC) by the change in SCC, for a simulated low SCC herd[1] that is offered premiums[2] for milk quality, after adoption of three different management practices.



[1]Low SCC = base of 109,000 cells/mL
[2]Premium = $0.0055/kg of milk
[3]Low cost = Most likely = $2.65/cow/yr with range from $0.40 to $6.20/cow per yr
[4]Moderate cost = Most likely = $11.32/cow/yr with range from $8.65 to 18.96/cow per yr
[5]High cost = Most likely = $14.60/cow/yr with range from $0.37 to $58.40/cow per yr

Figure 2.5. The change in cost ($/farm per yr) from reducing herd somatic cell count (SCC) by the change in SCC, for a simulated low SCC herd[1] that is not offered premiums for milk quality, after adoption of three different management practices.



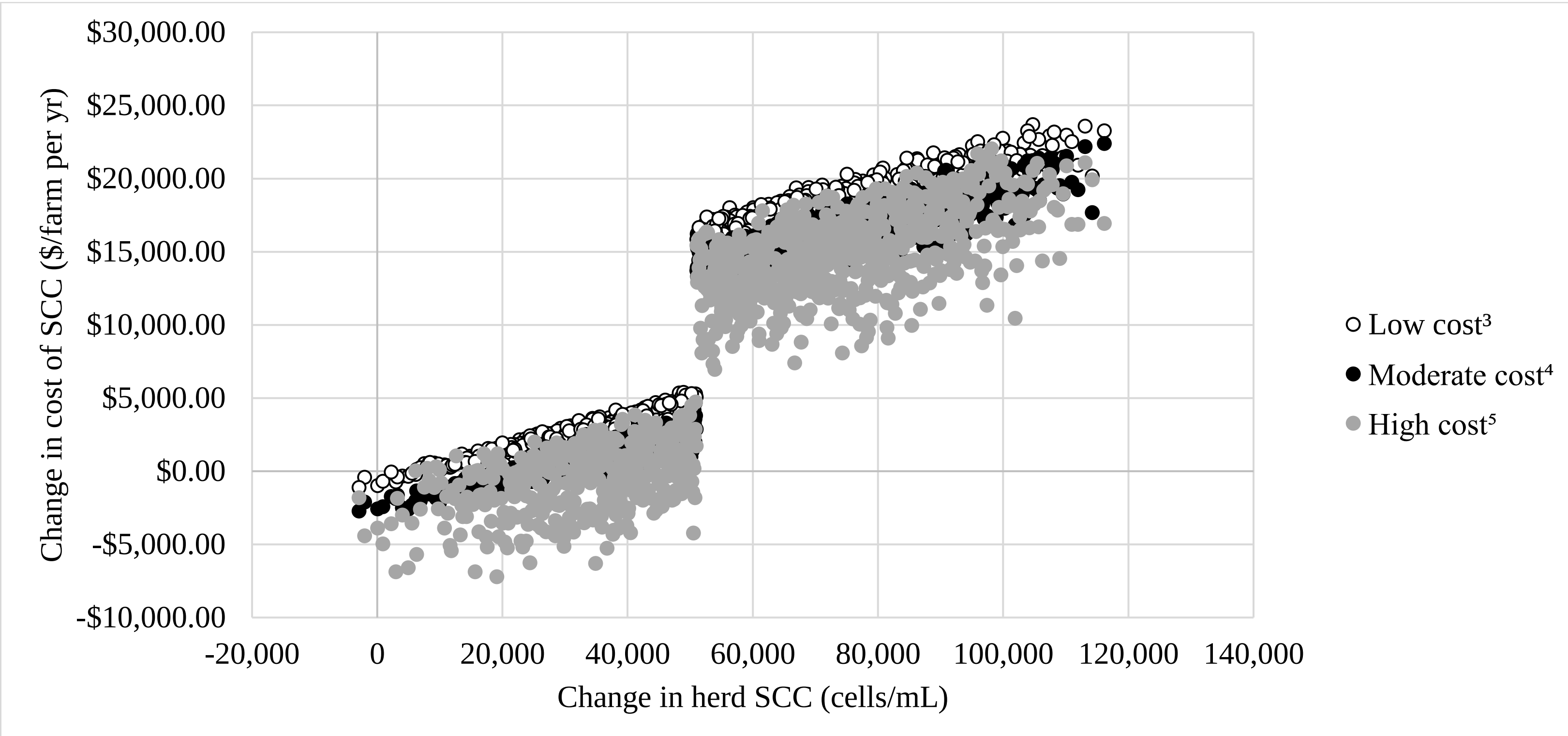
[1]Low SCC = base of 109,000 cells/mL

[2]Low cost = Most likely = $2.65/cow/yr with range from $0.40 to $6.20/cow per yr

[3]Moderate cost = Most likely = $11.32/cow/yr with range from $8.65 to 18.96/cow per yr

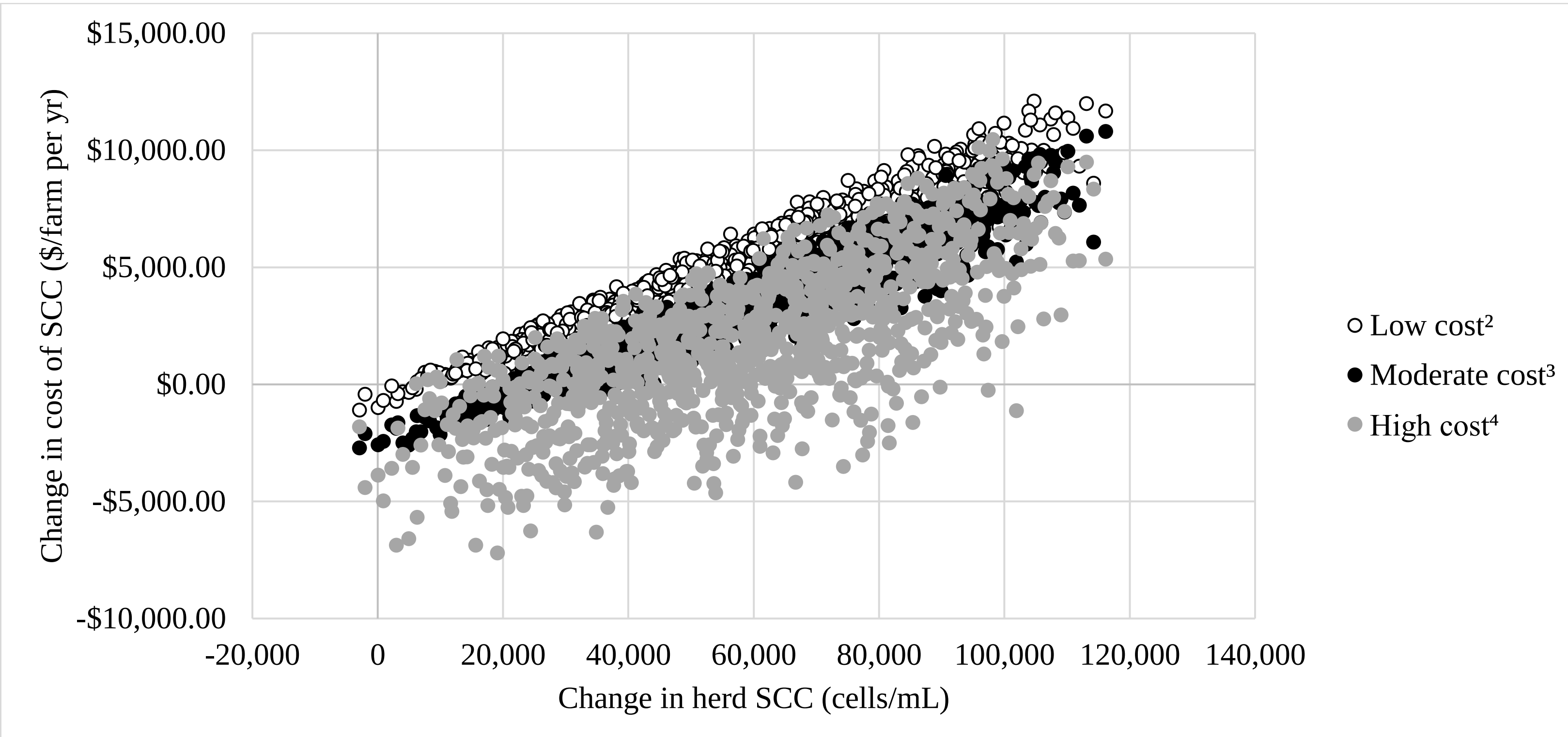
[4]High cost = Most likely = $14.60/cow/yr with range from $0.37 to $58.40/cow per yr

Figure 2.6. The change in cost ($/farm per yr) from reducing herd somatic cell count (SCC) by the change in SCC, for a simulated average SCC herd[1] that is offered premiums[2] for milk quality, after adoption of three different management practices.



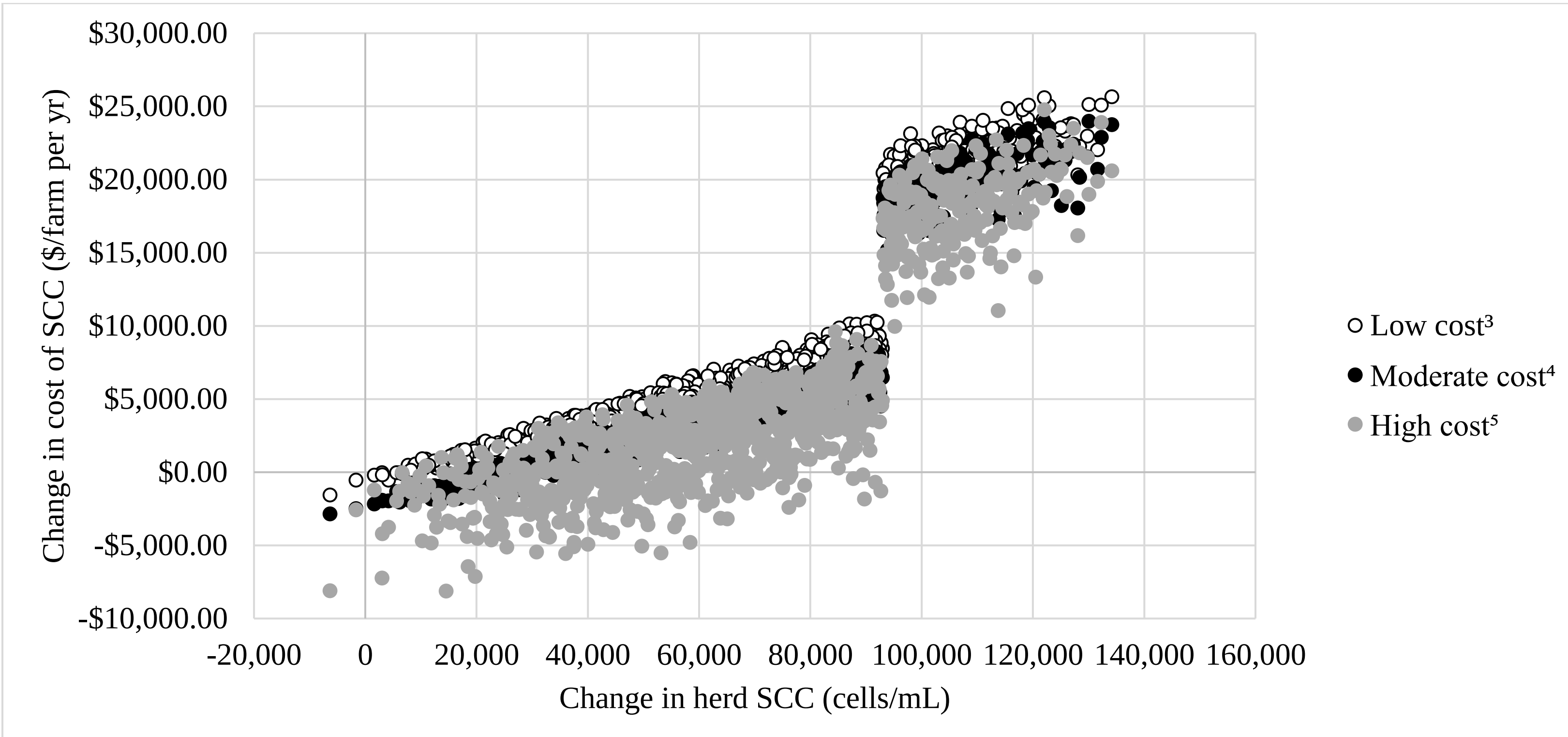
[1]Average SCC = base of 251,000 cells/mL
[2]Premium = $0.0055/kg of milk
[3]Low cost = Most likely = $2.65/cow/yr with range from $0.40 to $6.20/cow per yr
[4]Moderate cost = Most likely = $11.32/cow/yr with range from $8.65 to 18.96/cow per yr
[5]High cost = Most likely = $14.60/cow/yr with range from $0.37 to $58.40/cow per yr

Figure 2.7. The change in cost ($/farm per yr) from reducing herd somatic cell count (SCC) by the change in SCC, for a simulated average SCC herd[1] that is not offered premiums for milk quality, after adoption of three different management practices.



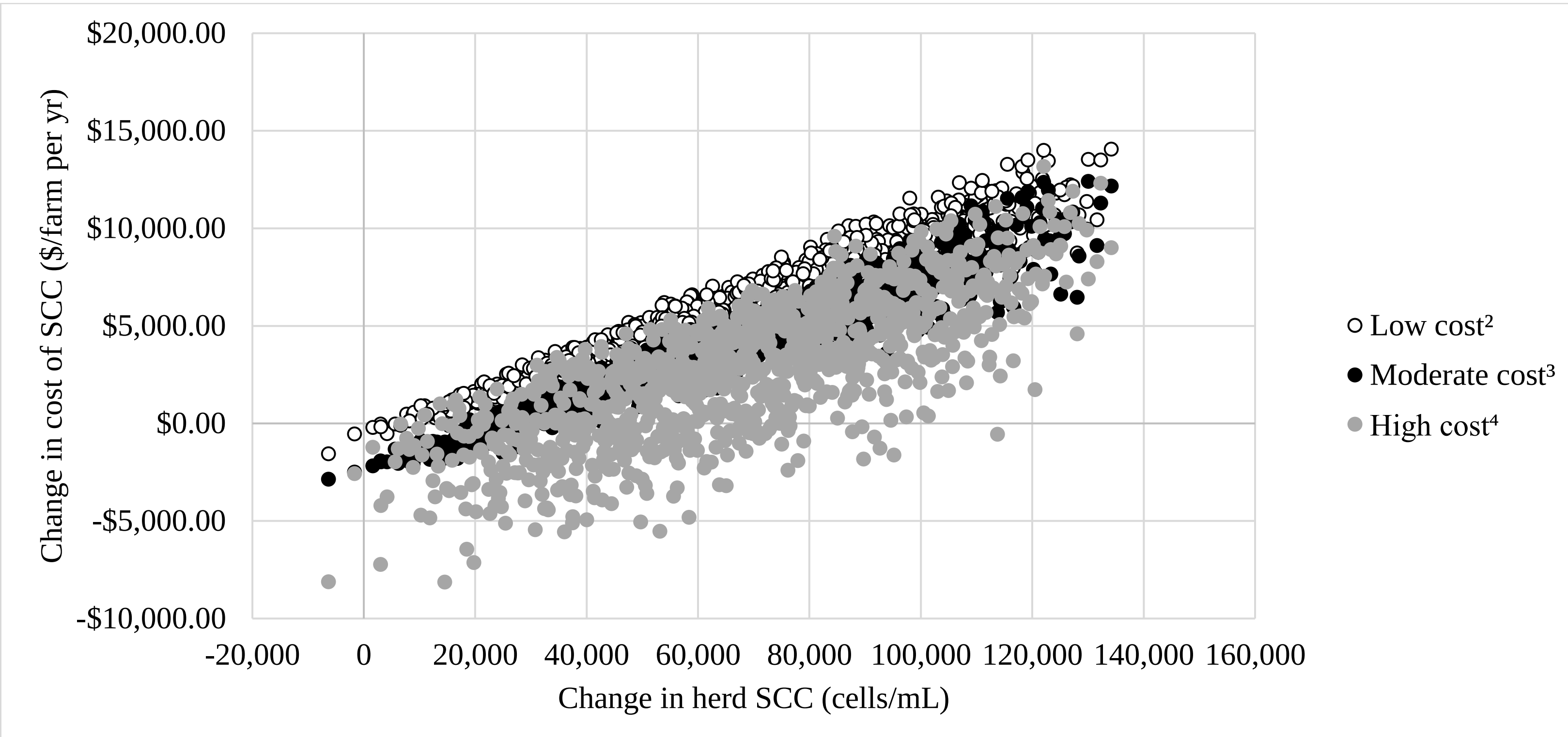
[1]Average SCC = base of 251,000 cells/mL
[2]Low cost = Most likely = $2.65/cow/yr with range from $0.40 to $6.20/cow per yr
[3]Moderate cost = Most likely = $11.32/cow/yr with range from $8.65 to 18.96/cow per yr
[4]High cost = Most likely = $14.60/cow/yr with range from $0.37 to $58.40/cow per yr

Figure 2.8. The change in cost ($/farm per yr) from reducing herd somatic cell count (SCC) by the change in SCC, for a simulated high SCC herd[1] that is offered premiums[2] for milk quality, after adoption of three different management practices.



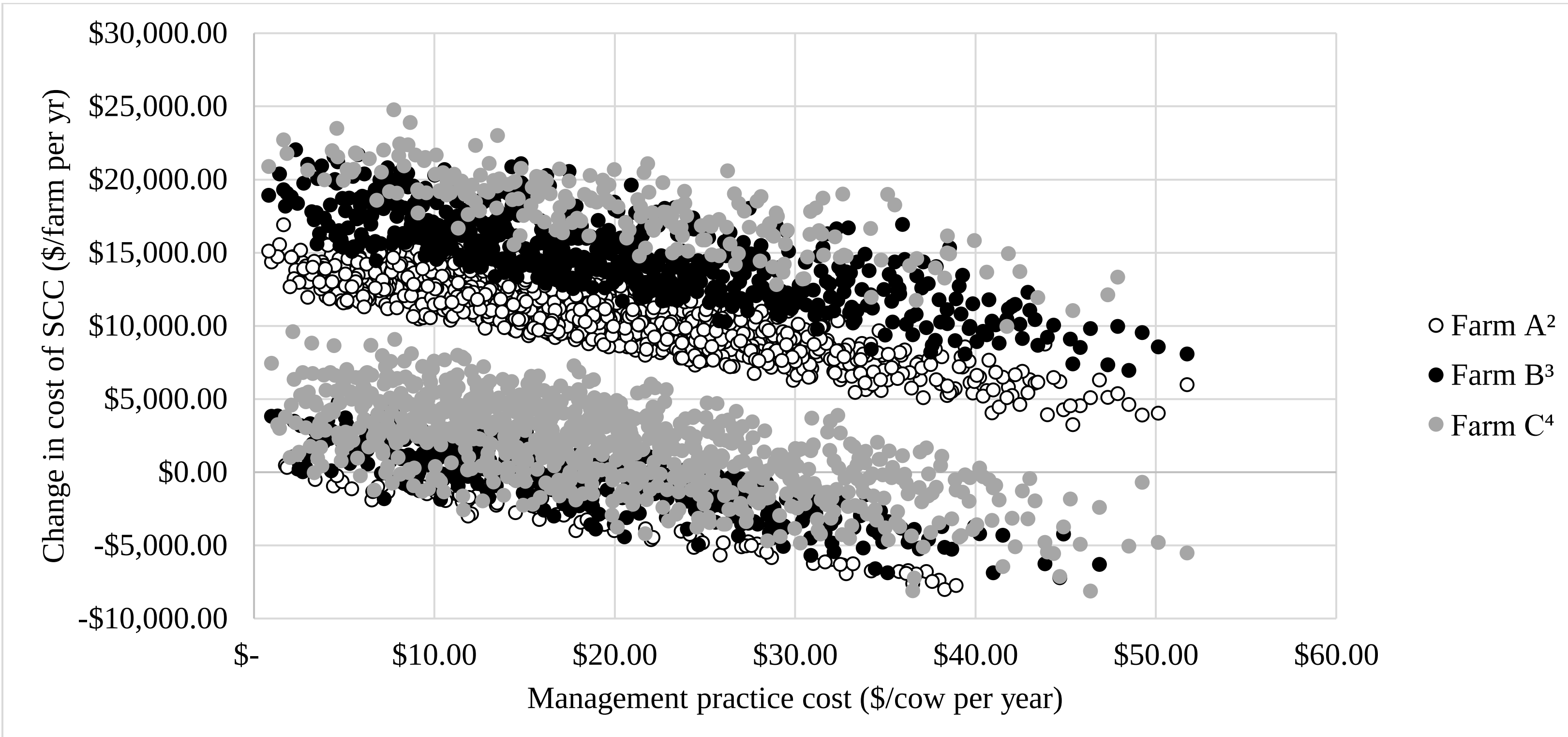
[1]High SCC = base of 393,000 cells/mL
[2]Premium = $0.0055/kg of milk
[3]Low cost = Most likely = $2.65/cow/yr with range from $0.40 to $6.20/cow per yr
[4]Moderate cost = Most likely = $11.32/cow/yr with range from $8.65 to 18.96/cow per yr
[5]High cost = Most likely = $14.60/cow/yr with range from $0.37 to $58.40/cow per yr

Figure 2.9. The change in cost ($/farm per yr) from reducing herd somatic cell count (SCC) by the change in SCC, for a simulated high SCC herd[1] that is not offered premiums for milk quality, after adoption of three different management practices.



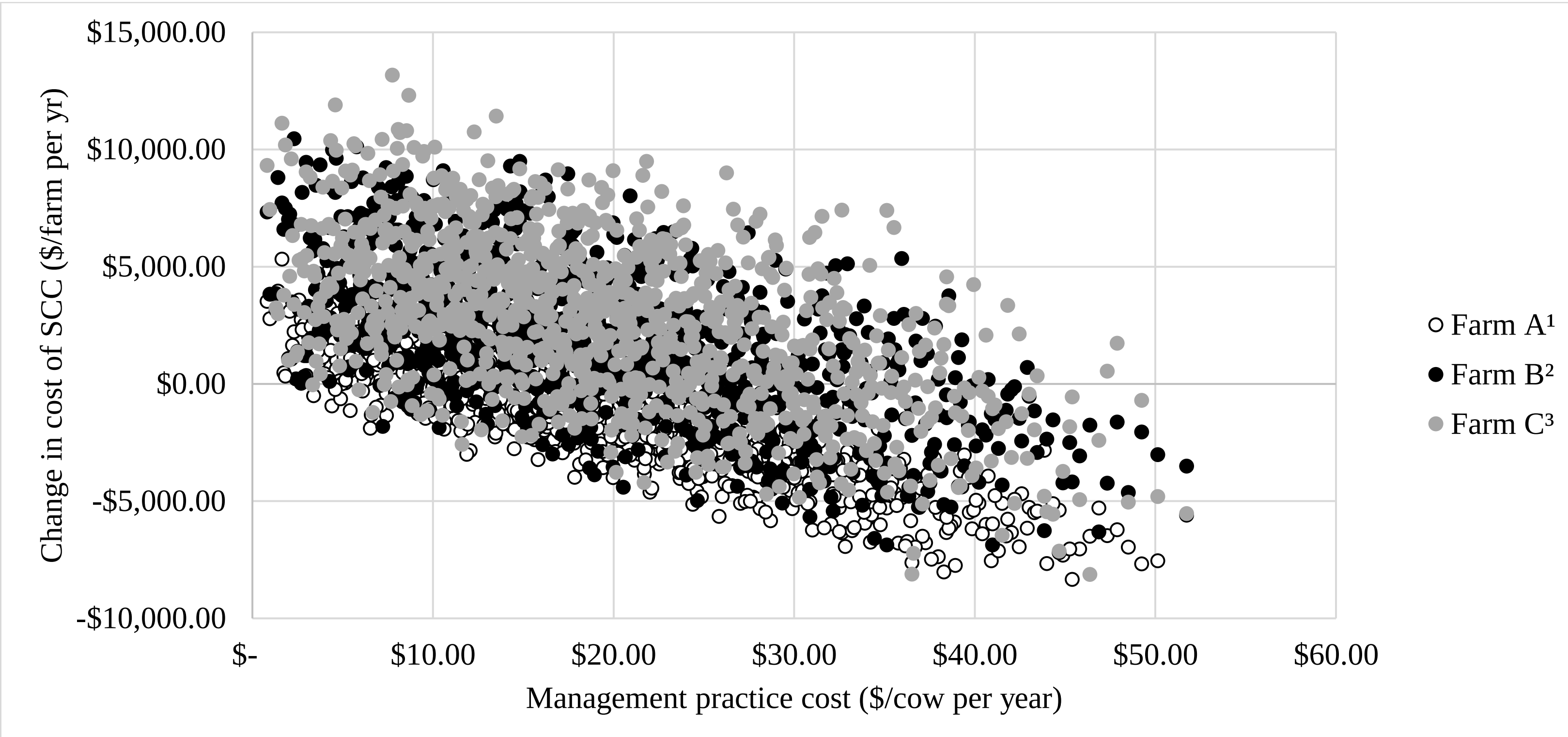
[1]High SCC = base of 393,000 cells/mL
[2]Low cost = Most likely = $2.65/cow/yr with range from $0.40 to $6.20/cow per yr
[3]Moderate cost = Most likely = $11.32/cow/yr with range from $8.65 to 18.96/cow per yr
[4]High cost = Most likely = $14.60/cow/yr with range from $0.37 to $58.40/cow per yr

Figure 2.10. The change in cost of somatic cell count (SCC) ($/farm per yr) from reducing herd SCC by management practice cost ($/cow per yr) for three simulated dairy farms that are offered a premiums for milk quality[1].



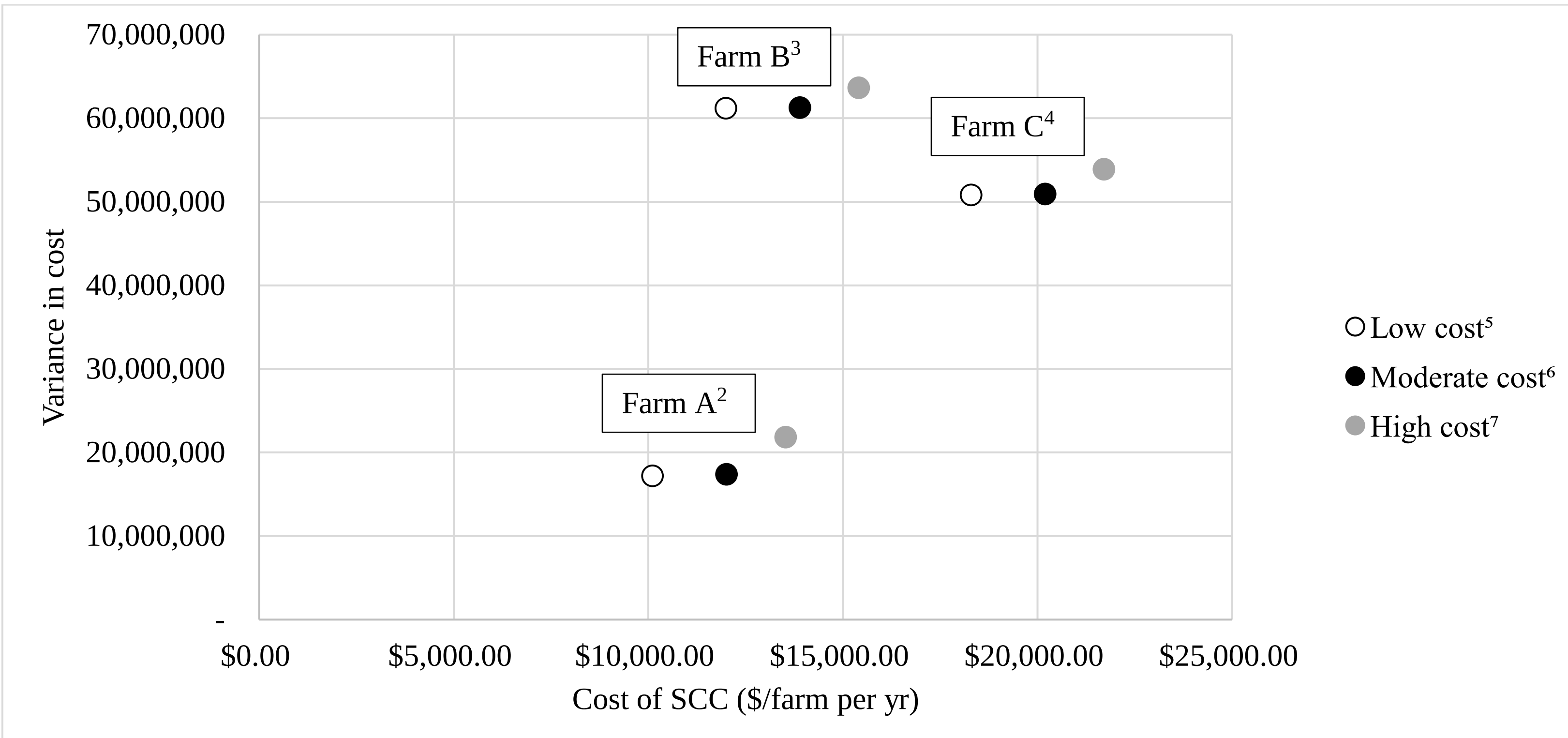
[1]Premium = $0.0055/kg of milk
[2]Farm A base SCC = 109,000 cells/mL
[3]Farm B base SCC = 251,000 cells/mL
[4]FarmC base SCC = 393,000 cells/mL

Figure 2.11. The change in cost of somatic cell count (SCC) ($/farm per yr) from reducing herd SCC by management practice cost ($/cow per yr) for three simulated dairy farms that are not offered a premiums for milk quality.



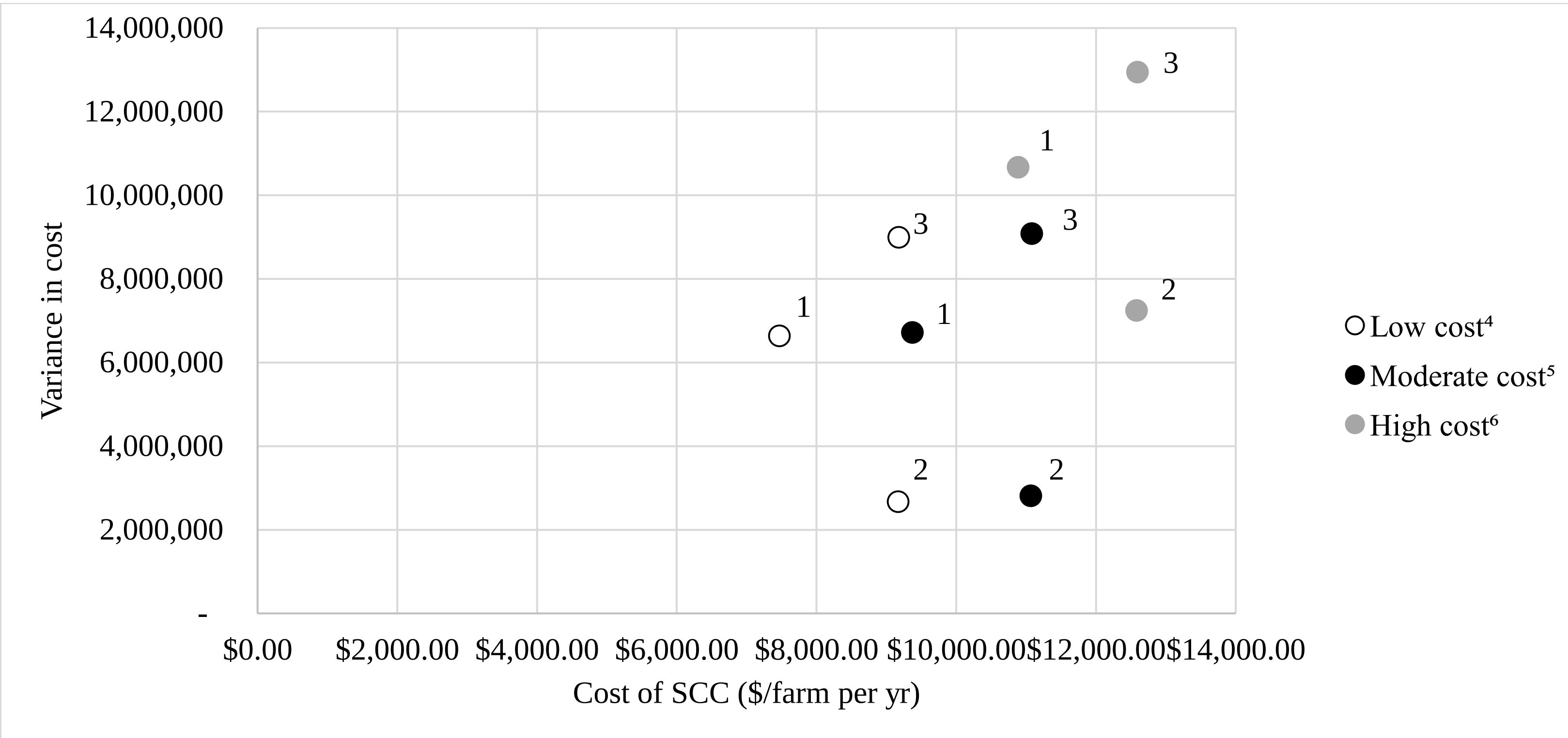
[1]Farm A base SCC = 109,000 cells/mL
[2]Farm B base SCC = 251,000 cells/mL
[3]FarmC base SCC = 393,000 cells/mL

Figure 2.12. The mean and variance of the cost of somatic cell count (SCC) ($/farm per yr) after adoption of management practices in three simulated dairy farms that are offered premiums for milk quality[1].



[1]Premium = $0.0055/kg of milk
[2]Farm A base SCC = 109,000 cells/mL
[3]Farm B base SCC = 251,000 cells/mL
[4]FarmC base SCC = 393,000 cells/mL
[5]Low cost = Most likely = $2.65/cow/yr with range from $0.40 to $6.20/cow per yr
[6]Moderate cost = Most likely = $11.32/cow/yr with range from $8.65 to 18.96/cow per yr
[7]High cost = Most likely = $14.60/cow/yr with range from $0.37 to $58.40/cow per yr

Figure 2.13. The mean and variance of the cost of somatic cell count (SCC) ($/farm per yr) after adoption of management practices in three simulated dairy farms that are not offered premiums for milk quality.



[1]Farm A base SCC = 109,000 cells/mL
[2]Farm B base SCC = 251,000 cells/mL
[3]FarmC base SCC = 393,000 cells/mL
[4]Low cost = Most likely = $2.65/cow/yr with range from $0.40 to $6.20/cow per yr
[5]Moderate cost = Most likely = $11.32/cow/yr with range from $8.65 to 18.96/cow per yr
[6]High cost = Most likely = $14.60/cow/yr with range from $0.37 to $58.40/cow per yr

3) CHAPTER THREE

A stochastic model comparing the economic benefit of blanket and selective dry cow therapies in a simulated United States dairy herd

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INTRODUCTION

Mastitis is one of the most common and costly diseases in the dairy industry (Hogeveen et al., 2011, Liang et al., 2017). Mastitis can be infectious or non-infectious in origin (Bradley, 2002). Non-infectious mastitis is typically caused by physical damage to the mammary gland while, more commonly, infectious mastitis is caused by microorganisms entering the gland. The most common microorganism that causes an intramammary infection is bacteria (Bradley, 2002). When signs of inflammation are visible, such as a swollen mammary gland or milk with clots or flakes, the intramammary infection is referred to as clinical mastitis **(CM)**. An intramammary infection with no visible signs of inflammation, but bacteria are present in the milk, is commonly known as subclinical mastitis **(SCM)** (Harmon, 1994). Historically somatic cell count **(SCC)** has been used to determine if a cow has SCM. When the SCC exceeds 200,000 cells/mL a cow is considered to have an intramammary infection (Natzke et al., 1972, Dohoo and Leslie, 1991, Jadhav et al., 2018). Though a SCC of greater than 200,000 cells/mL is associated with an intramammary infection, milk loss can occur at SCC lower than 100,000 cells/mL (Raubertas and Shook, 1982, Gonçalves et al., 2018, Hadrich et al., 2018).

Cows are most at risk for both CM and SCM during the dry period (Neave et al., 1950, Erb et al., 1984, Pantoja et al., 2009a). To control mastitis, the National Mastitis Council developed a 5-point plan to prevent new mastitis cases (Dodd and Neave, 1970) that is still used as a guide today (Hillerton and Booth, 2018). One of the components of the plan is treating every quarter of every cow with an intramammary antibiotic **(IMMA)** at dry off, commonly referred to as blanket dry cow therapy **(BT)**.

Dry cow therapy **(DCT)** has two goals: 1) to prevent new intramammary infections during the dry period and 2) to treat existing intramammary infections at the time of dry off. As of 2014, 80.3% of surveyed dairy farmers in 24 states of the United States **(US)** were treating all quarters of all cows at dry off (USDA Animal and Plant Health Inspection Service, 2016). Because of highly debated use of antibiotics in animal agriculture, pressure is being put on policymakers to limit antibiotic use (Croney et al., 2012). Antibiotic regulation within the dairy industry has resulted in some countries, such as the Netherlands, Australia, and New Zealand, to discontinue the use of DCT to prevent new intramammary infections (Lam et al., 2017, McDougall, 2018). Instead, farmers select cows that are to receive antibiotic treatment at dry off based on infection status of the cow. This form of DCT is commonly referred to as selective dry cow therapy **(ST)**.

Selective dry cow therapy has been shown to have positive results compared to no treatment with decreased incidences of new intramammary infections at calving at the cow and quarter level (Halasa et al., 2009b, Halasa et al., 2009c). However, BT offered more protection than ST (Berry and Hillerton, 2002, Halasa et al., 2009c). The success of ST may depend on the infection status of the mammary gland at dry off. Cows that have a SCC greater than 200,000 cells/mL at dry off are more likely to have a case of CM in the following lactation (Pantoja et al., 2009a, Henderson et al., 2016). The difference in protection raised questions of how BT and ST compare economically and how selection criteria for ST affect the economics of DCT.

Economic analyses between the two DCT methods have been completed by researchers in Great Britain and the Netherlands where ST is required (Berry et al., 2004, Scherpenzeel et al., 2016, Scherpenzeel et al., 2018). Results of these studies have shown that little difference exists between the costs of BT and ST and that mastitis incidence throughout the dry period and early in the next lactation play a crucial role in the selection of the preferred practice.

Though many economic analyses have been completed comparing the costs of BT and ST, little research has been done modeling the US dairy system. A gap in the literature also exists in determining how input costs and herd demographics might influence economic outcomes. The objectives of our study were to 1) determine the costs of BT and ST in a simulated US dairy herd, 2) determine if different selection criteria would lead to decreased costs of ST compared to BT, and 3) to determine how input costs and herd demographics would impact optimal DCT decisions.

MATERIALS AND METHODS

Model Overview

A stochastic simulation model was created using Microsoft Excel (Microsoft Corporation, Redmond, WA) with @Risk add-in (Palisade Corporation, Ithaca, NY). The simulation model was developed to model different dry off therapy schemes in a simulated US dairy herd. Five different dry off schemes were modeled based on dry off SCC and parity. Dry-off therapy schemes included blanket dry cow therapy **(BT)**, no therapy **(NT)**, and three ST schemes that were based on the SCC groups shown in Table 3.1. For each of the three ST schemes only certain SCC groups received treatment with antibiotics at dry off. Treatment of groups 4 and 9 were considered ST scheme 1 **(ST1)**, treatment of groups 3, 4, 8, and 9 were considered ST scheme 2 **(ST2)**, and treatment of groups 2, 3, 4, 7, 8, and 9 were considered ST scheme 3 **(ST3)**. With BT serving as the base, costs of NT and the three ST schemes were compared to the cost of BT.

Herd Demographics

Dairy herd data were collected from Dairy Records Management Systems **(DRMS)** (Dairy Records Management Systems, Raleigh, NC). When collecting information from the DRMS database, the only limit option used was "breed" to only include Holsteins. The average Holstein herd enrolled in the DRMS program as of December 2018 consisted of 205 cows with a SCC of 251,000 cells/mL and a cull rate of 38.6%. To model herds with differing SCC, two additional herds were analyzed by taking one standard deviation from the mean SCC (251,000 cells/mL). A low SCC herd had a SCC of 109,000 cells/mL, and a high SCC herd had a SCC of 393,000 cells/mL.

Somatic Cell Count Groups

Using DRMS test day data, distributions of cows within each of the nine SCC groups were created for the three herds. To create the distributions, the following analysis was completed in SAS 9.4 (SAS Institute, Cary, NC). Test day data from every cow in every herd enrolled in DRMS (n = 18,151) were compiled from January 2015 to December 2017. To be included in the analysis, Holstein cows had to have data from at least four test days within a single lactation and a lactation length between 240 and 365 days. To remove any outliers in the dataset, cows must also have been within two standard deviations of the average lactation age and greater than the first percentile in lactation milk yield. Only the most recent lactation was analyzed for those cows that completed two lactations within two years. Herds that did not have at least five cows that met those criteria were deleted from further analysis (n = 7,393). Similar cleaning analyses were used by Raubertas and Shook (1982) and Nolan (2017) when working with test day SCC data.

Three separate datasets were created based on the average weighted SCC of the herds throughout 2016. Herds that did not have 2016 herd SCC data were removed from the datasets (n = 2,984). Datasets included herds with SCC ≤ 109,000 cells/mL (n = 1,840), 109,000 cells/mL < SCC < 393,000 cells/mL (n = 3,738), and SCC ≥ 393,000 cells/mL (n = 2,196). Using the FREQ procedure in SAS 9.4, each of the three datasets were analyzed to determine the percentages of cows that fell into the nine SCC groups based on their SCC on the last test day of the lactation before dry off (Table 3.1). To determine the total number of cows that would be dried off throughout the year, the percentage that fell into each group was multiplied by the herd size times the culling rate. Like Scherpenzeel et al. (2018), authors also assumed that 10% of the cows being culled would have been dried off before culling. Given that the average herd simulated had 205 cows with a cull rate of 38.6%, 133 cows were assumed to be dried off throughout the year.

Cost of Dry Cow Therapy

Drug Cost. The authors assumed that every cow that was designated to be treated received 4 tubes of IMMA, while cows in the NT group did not. The cost of treatment totaled $11.32/cow for antibiotics (Valley Vet Supply, 2018). The total treatment cost to the herd was calculated using the following formula:

$$TC\$ = T * C$$

Where:

TC$ = The total cost of treatment per herd per year

T = The cost of treatment (IMMA) ($/cow)

C = The number of cows treated annually

Labor Cost. Labor costs differed between BT and ST. The authors assumed that BT would be administered in the parlor at dry off by milking labor. Selective dry cow therapy would be administered outside of the milking parlor by management labor. The hourly wage was $12.47/hr for milking labor and $33.47/hr for management labor (Bureau of Labor Statistics, 2019). The authors assumed, based on experience, that the time for treatment was 0.16 and 0.25 hours/cow for BT and ST, respectively. Though inputs for the cost of labor were different between the two treatment options, the formula was the same:

$$L\$ = W * H * C$$

Where:

L$ = The total labor cost per herd per year

W = Hourly wage ($/hr)

H = Hours per cow

C = Number of cows treated

Mastitis Incidence Rates. Little research examining the effect of using multiple SCC thresholds as selection criteria for IMMA at dry off on mastitis incidence rate has been completed. Scherpenzeel et al. (2018) estimated mastitis incidence rates using two different data sources (Barkema et al., 1998b, Scherpenzeel et al., 2014). Data from Barkema et al. (1998b) and Scherpenzeel et al. (2014) were collected from farms in the Netherlands. To adapt the SCC groups used by Scherpenzeel et al. (2018), authors created an index value to estimate mastitis incidence rates based on SCM incidence rates from DRMS data.

Subclinical mastitis incidence rates were derived by performing further analysis on the three datasets used in the "Somatic Cell Count Groups" section of this paper. To qualify for further analysis, cows in each of the three datasets needed to have test day data from either the first or second test day of the next lactation (n = 581,232) representing the first test of the lactation. If the first test day of the cow's lactation was greater than 100 days in milk (n = 384), they were removed from the dataset. Cows that had a first test day somatic cell count above 200,000 cells/mL were considered to have SCM (n = 89,993). Using the FREQ procedure in SAS, the incidence of SCM was determined for each dry off SCC group.

Within CM and SCM groups, incidence rates were also different between cows that did **(CM(+)/SCM(+))** and did not **(CM(-)/SCM(-))** receive IMMA at dry off. The infection rate derived from the DRMS data was used as the SCM (+) incidence rates (Table 3.2). Because the dry off procedures of DRMS data were not known, authors assumed all cows in the DRMS dataset received intramammary antibiotics at dry off (SCM(+)). To account for the incidence rates of the CM(+), CM(-), and SCM(-) categories, an index value was created using the SCM(+) incidence rates collected from the DRMS data along with the incidence rates presented by Scherpenzeel et al. (2018). Index values were created using the following equation:

$$IIR = \frac{SIR}{SSCM(+)} * DSCM(+)$$

Where:

IIR = Index incidence rate (%)

SIR = Incidence rates (%) for CM or SCM presented by Scherpenzeel et al. (2018)

SSCM(+) = Subclinical mastitis incidence rate (%) for cows receiving intramammary antibiotics at dry off presented by Scherpenzeel et al. (2018)

DSCM(+) = Subclinical mastitis incidence rate (%) for cows receiving intramammary antibiotics at dry off derived from Dairy Records Management Systems data

The equation was used to determine the estimated incidence rates at calving for dry off SCC groups 4 and 9 for CM(+), CM(-), and SCM(-). To calculate the incidence rates for the remaining dry off SCC groups, the percent change in incidence rate starting with groups 4 and 9 from each succeeding group was calculated from the incidence rates derived from the DRMS data. The change in incidence rate from each SCC dry off group was then applied to the CM(+), CM(-), and SCM(-) categories (Table 3.2). An example of the calculation used to determine the estimated incidence rates is shown in the Appendix (Tables A.2 to A.8).

Mastitis Costs. The cost of clinical mastitis was derived from Rollin et al. (2015), with an average cost of $444/case (2015 US$). Subclinical mastitis cost was calculated independently for each SCC group based on milk loss throughout the lactation associated with an increase in the first test SCC (Nolan, 2017). Average milk loss associated with a first test SCC between 200,000 and 1,600,000 cells/mL was 68 kg per lactation for each increase in 100,000 cells/mL when averaged across parities 2 and 3. Milk loss was then multiplied by the 2019 average uniform milk price to date as of September 2019 ($0.38/kg) (USDA Agricultural Marketing Service, 2019) to get an average cost per case of subclinical mastitis of $25.84 per case. The total cost of mastitis to the farm was calculated using the following formula across all five DCT schemes:

$$MC\$ = \sum_{i=1}^{9} CM * I_{CM} * C + SCM * I_{SCM} * C$$

Where:

MC$ = Total mastitis cost ($/farm per yr)

CM = Clinical mastitis cost ($/case)

I_{CM} = Incidence rate of clinical mastitis (%)

C = The number of cows in each of the nine SCC dry off groups

SCM = Subclinical mastitis cost ($/case)

I_{SCM} = Incidence rate of subclinical mastitis (%)

Total therapy costs for each of the 5 DCT schemes were calculated with the following formula:

$$DCT\$ = TC\$ + L\$ + MC\$$$

Where:

DCT$ = The total cost of dry cow therapy per herd per year

TC$ = Total treatment cost per herd per year

L$ = Total labor costs per herd per year

MC$ = Total mastitis costs per herd per year

Though the total cost of DCT were calculated with the same base formula above, slight changes were made to accommodate each DCT scheme. Labor costs for each ST scheme were only summed across the cows that were treated with IMMA at dry off. Total costs for NT did not include the costs for drugs or labor because of the lack of treatment. However, they did include the costs associated with mastitis in the next lactation.

Simulation

A single 1,000-iteration simulation was run collecting output variables, including the total cost of BT, NT, ST1, ST2, and ST3 therapy schemes. The differences between BT and all other therapy schemes were also collected. Input variables included CM and SCM costs, estimated time of treatment for both BT and ST schemes, and labor costs associated with BT and ST schemes. A PERT distribution was fit to all input variables (Table 3.3). The distribution around the cost of CM was derived from Rollin et al. (2015), and the cost of SCM was derived by taking the minimum and maximum milk loss presented by Nolan (2017) times the milk price. Because milk loss makes up the majority of the costs associated with mastitis (Huijps et al., 2008, Halasa et al., 2009a, Liang et al., 2017), authors assumed that costs of CM and SCM would both increase or decrease from iteration to iteration during a simulation. To account for both costs moving in the same direction during the simulation, a 90% @Risk correlation coefficient was set between the two variables. Distributions for labor costs were not presented by Bureau of Labor Statistics (2019), so they were estimated by authors based on known labor costs. Minimum and maximum values for the time of treatment were rounded to the nearest hundredths place and values for wages were rounded to the nearest $0.50.

A PERT distribution was also fit to the incidence rates of mastitis with the minimum being half the original value and the maximum being double the most likely (original) value (Table 3.4). Values in Table 3.4 were rounded to the nearest tenths place. The weighted average CM and SCM incidence rates were calculated for each DCT option (Table 3.5). Weighted averages were formulated by taking the percentage of cows in each SCC group for all three herds and multiplying by the respective incidence rates associated with the treatment scheme. For example, when calculating the weighted average incidence rate for ST1, the percentage of cows in dry off groups 4 and 9 were multiplied by the incidence rates associated with treating those cows. The percentage of cows in the remaining groups were multiplied by the incidence rates associated with no treatment. The incidence rates of each SCC group were then summed together resulting in the weighted average incidence rate. Weighted average incidence rates corresponding to each treatment scheme were then compared to BT to determine the difference needed for each DCT scheme to cost less than BT.

The simulation was run using Latin Hypercube sampling with a static seed of 31,517 (Liang, 2013, Nolan, 2017, Dolecheck, 2018). After the simulation, a frequency analysis was completed on the differences in costs of treatment schemes. With BT serving as the base, the frequency analysis was completed to determine the percent of iterations in which BT was the lowest-cost treatment option.

Statistical Analysis

Results from the simulation for the total cost of each of the 5 DCT were analyzed for significant difference across each of the three herd types. Analyses were completed using Microsoft Excel Simetar (Simetar, College Station, TX) add-in. The means of each DCT cost were compared to one another, by herd type, using a two-sample T-test to determine significant differences at $P < 0.05$.

Sensitivity Analysis

An objective of this study was to determine what factors affect the economics of different treatment schemes. To accomplish this, multiple simulations were run by changing the PERT distribution around each input variable. Additional simulations were run in which a PERT distribution was created around the herd size, making it a stochastic variable. Different scenarios were evaluated through simulation by modifying the distributions to determine their sensitivity. After each simulation, a frequency analysis was completed to determine the change in frequency that BT was the lowest-cost treatment option.

RESULTS

Overall Simulation

Regardless of herd SCC, BT had the lowest average cost, while NT was the highest across all three simulated herds (Table 3.6). The mean cost of BT was significantly lower ($P < 0.05$) than all other DCT schemes across all herd types (Table 3.6). Overall costs ranged from $10,637.35 (BT, low SCC herd) to $14,685.33 per herd per year (NT, high SCC herd). When comparing the differences in costs of each treatment scheme to BT, ST3 had the least difference in cost across all herd types (Table 3.7). Of the three ST schemes, ST3 had a significantly lower ($P < 0.05$) mean cost across all three herd types, suggesting that the more cows that received intramammary antibiotics at dry off, the less the DCT scheme would cost the farm. The total costs of DCT in all schemes increased across all three herds as average SCC increased (Figure 3.1). However, the high SCC herd experienced the least difference between BT and ST2 and ST3 (Figure 3.2). Some iterations resulted in other DCT schemes costing less than BT. However, BT was optimal in greater than 82% of the iterations across all DCT schemes and herd types (Figure 3.3).

When the incidence rate for mastitis was held constant, and only the cost variables were changed, the cost of CM and SCM led to the most variation in the differences between the cost of BT and the other treatments. When examining the difference between BT and ST1 for the low SCC herd, CM cost had the greatest impact on the difference between the two DCT costs (Figure 3.4). When examining just the difference between BT and ST1 for the low SCC herd, the average difference was $1,506.64. Because of the variation in CM cost, the difference between BT and ST1 could range from $601.10 to $2,441.93. As shown in Figure 3.4, none of the cost related inputs alone led to BT costing more to a farm than ST1. These results were consistent across all DCT schemes. So, additional simulations were run changing the distribution of one variable at a time, while holding the others in a constant state, to determine at what value each variable led to iterations in which BT costs were not lower than other treatment decisions in 100% of the iterations run. The distributions were changed with each simulation to find a distribution large enough in which BT resulted in a higher cost than other DCT schemes. Authors stopped running simulations when they felt that the distributions around each variable were becoming unrealistic.

Clinical Mastitis Cost

Two simulations were run in which CM cost was the only stochastic input, while all other variables were held constant. In the first simulation, the distribution of CM cost was kept as the original used in the model with the cost of CM ranging from $244.00 to $644.00. All of the iterations in the first simulation resulted in BT having the lowest cost across all herd types and DCT schemes. When the size of the distribution was increased to a range from $111.00 to $777.00, BT was no longer optimal in all iterations. Using the larger distribution resulted in NT, ST1, ST2, and ST3 DCT schemes having a lower cost than BT in some scenarios (Figure 3.5) across the three different SCC herds. The maximum cost of a CM case in the iterations in which BT was no longer optimal differed between DCT scheme and herd type (Tables 3.8, 3.9, and 3.10). Selective therapy scheme 3 needed the lowest CM cost to become more economical than BT regardless of herd SCC (Figure 3.6). For the high SCC herd, ST3 did not have any iterations in which the cost of ST3 was lower than BT. In the low and average SCC herds, associated with the inputs modeled, the cost of CM would have to be below $166.56 and $123.30, respectively, before producers should consider switching from BT to ST3 (Tables 3.8 and 3.9).

Figure 3.7 displays the relationship between the cost of CM and the difference between BT and ST3 for the low SCC herd. When examining the differences in the costs of BT and ST3 for a low SCC herd, the difference in cost between the two treatments increased as the cost of CM decreased. This trend is similar across all treatment and herd types.

Subclinical Mastitis Cost

Multiple iterations were run in which the distributions of SCM costs increased. Though SCM costs accounted for a large variation in the differences in the costs of BT and other treatment schemes, as shown in Figure 3.4, when modeled alone, none of the iterations led to a scenario in which BT was not the optimal treatment decision. The lack of iterations in which BT was not optimal may be because of the lower costs associated with SCM compared to CM.

Labor Cost

Both changes in labor wages and hrs associated with ST were simulated. However, after multiple simulations, none of the iterations resulted in BT being higher in costs than any of the other treatment methods. Authors decided to stop simulations as wages and time became unrealistic. Instead, additional simulations were run with BT labor.

Though reaching unrealistic values, authors continued to run simulations to determine what wages and time would lead to iterations in which BT was not the lowest cost across all treatment types. The labor wage and time of treatment in which BT was no longer optimal was dependent on DCT scheme. A simulation was run where labor wages associated with the BT scheme ranged between $10.50 and $90.00/hr that resulted in iterations in which BT was no longer the lowest-cost treatment option across all DCT schemes and herd types. Wages had to increase to a cost of $81.10, $83.70, and $84.06/hr before ST1 would cost less than BT for low, average, and high SCC herds, respectively (Tables 3.8, 3.9, and 3.10). For all herd types, even with a distribution including $90.00/hr for labor, NT never resulted in a lower cost than BT (Figure 3.8). When comparing BT to the ST schemes, labor wages for BT had to increase the least for ST3 to become the optimal treatment decision (Figure 3.9). At an hourly wage of $70.52, $70.24 and $69.65/hr ST3 would cost less than BT for low, average, and high SCC herds, respectively. Figure 3.10 displays the relationship between the increase in labor wages and the difference between BT and ST3 costs. At the time of the current study where $70.00/hr is an unrealistic wage, labor wages should not be a deciding factor when considering BT to other DCT schemes.

When including a distribution of time ranging from 0.08 to 0.50 hrs, BT was not the lowest cost treatment scheme in all iterations. Blanket therapy was still optimal in 100% of iterations when compared to NT. However, all three ST schemes were optimal at times (Figure 3.11). Regardless of herd SCC, the time of treatment in which BT was no longer optimal were similar (Tables 3.8, 3.9, and 3.10). When treatment times were 0.39, 0.40, and 0.40 hrs, ST1 would cost less than BT for low, average, and high SCC herds. The time to complete BT had to increase the least for ST3 to become optimal (Figure 3.12). Blanket therapy treatment could take 0.34, 0.34, and 0.33 hrs before ST3 would become more feasible for low, average, and high SCC herds, respectively (Tables 3.8, 3.9, and 3.10). As BT time increased, the difference in cost between ST3 and BT decreased (Figure 3.13).

Herd Size

Additional simulations with herd size fit to a PERT distribution were run to determine if herd size affected DCT decisions. However, after simulations included a distribution of 20 to 7,000 cows in which BT was still the optimal treatment option in 100% of iterations, authors stopped the herd size analysis.

Mastitis Incidence Rate

An additional simulation was run where all costs were held constant, and only CM and SCM incidence rates were treated as stochastic variables. The distribution of CM and SCM incidence rates (Table 3.4) ranged from half to double the estimated most likely incidence rate value for each SCC group. Values in Table 3.4 were rounded to the nearest tenths place. Frequencies in which BT was the lowest cost DCT scheme ranged from approximately 88% to 98% depending on the DCT scheme being compared and herd SCC (Figure 3.14).

When using NT, clinical mastitis incidence rates had to be within 2.1% of the incidence rate of BT for NT to be feasible (Table 3.8). These incidence rates decreased with the use of the ST schemes (Table 3.8, 3.9 and 3.10). Selective dry cow therapy scheme 3 needed to have incidence rates closest to BT to be economically feasible across all herds (Figure 3.15). When ST3 cost less than BT, the incidence rates for ST3 were within 1.0%, 0.7%, and 0.1% of the BT incidence rates for low, average, and high SCC herds, respectively (Tables 3.8, 3.9, and 3.10). As the difference in CM incidence rates increased between ST3 and BT, the difference between the total cost of the therapies increased across all herds (Figure 3.17). This relationship was similar for SCM.

The incidence rate of SCM when using ST3 had to be within 12.5% of BT for ST3 to cost less than BT in the high SCC herd (Table 3.10). The difference in incidence rates were higher for low and average SCC herds (Figure 3.16). To have the lower cost compared to all other treatment options, NT required the least difference in incidence rates from BT (Tables 3.8, 3.9, and 3.10).

DISCUSSION

Recently, ST has become a mandatory practice in multiple countries, such as the Netherlands and Australia (Lam et al., 2017, McDougall, 2018). For this reason, multiple studies have been completed examining the costs and economic benefits between BT and ST (Berry et al., 2004, Huijps and Hogeveen, 2007, Scherpenzeel et al., 2016) with the most recent study being completed by Scherpenzeel et al. (2018). However, little research has focused on a US dairy system.

Past models can be used as a reference when determining the benefit of ST to US dairy farms, but many differences exist between the US dairy systems and other systems around the world. One of the main differences is that the size of the herd modeled is different than those in the United Kingdom and Netherlands models. Both Scherpenzeel et al. (2016) and Scherpenzeel et al. (2018) modeled a Dutch herd with an average of 100 cows, while the herd modeled in our study was a 205-cow Holstein herd. Other differences are within the modeling schemes, such as dry off treatment decision processes and individual model inputs.

Berry et al. (2004) compared the benefits of BT and ST using a decision tree model at the cow level rather than a herd level in the United Kingdom. By doing so, Berry et al. (2004) were able to determine optimal treatment decisions on a cow by cow basis by taking into account pathogen-specific decisions as well. Berry et al. (2004) concluded that the cost of DCT averaged from $51.84 and $114.54 per cow per year (2019 US$) for cows that did and did not receive treatment, respectively. The large range in the results presented by Berry et al. (2004) may be due to the modeling of different mastitis pathogens. Our results fall into the range presented by Berry et al. (2004), with a range of $51.88 to $71.63 per cow per year (2019 US$) depending on the herd type and treatment used. One reason for the difference in the variation in costs between the current model and the model presented by Berry et al. (2004) is due to the difference in modeling types. Berry et al. (2004) modeled at the cow level with bacterial culture being the deciding factor of whether a cow received antibiotics at dry off or not. Taking milk cultures of cows before dry off allows farmers to make a more educated DCT decision at the cow level. However, taking the culture takes time and adds expenses. The additional expenses of culturing and the cost associated with specific bacteria types could be the reason for the larger variation in cost presented by Berry et al. (2004). Bacteria type has an effect on the total cost of mastitis because of pathogen-specific milk losses and response to treatment (Pinzon-Sanchez et al., 2011, Nolan, 2017). Another difference was the modeling of treatment decisions using specific cow information rather than generalizing treatment decisions across a dairy herd. Other models have looked at a whole herd approach.

Huijps and Hogeveen (2007), Scherpenzeel et al. (2016), and Scherpenzeel et al. (2018) have all modeled the costs and benefits of BT vs. ST in a Dutch system. Similar modeling techniques were used in all three studies as were used in the current analysis. Somatic cell count groups, CM incidence rates, and SCM incidence rates were modeled very similarly to Scherpenzeel et al. (2016) and Scherpenzeel et al. (2018). However, we believe incidence rates were one of the most limiting factors in the model. Very little research has been done examining the incidence rates of mastitis in the next lactation when DCT is administered based on SCC. Though research in the US has been completed on selection criteria on dry cow therapy success (Patel et al., 2017, Vasquez et al., 2018), authors could find no US studies that had broken ST dry off decisions by nine different dry off SCC groups. Scherpenzeel et al. (2018) used two different sources when determining mastitis incidence rates for their model.

In our analysis, we decided to use the CM and SCM incidence rates presented by Scherpenzeel et al. (2018) as a base while trying to account for differences in incidence rates in the US. Though limited potentially by herd demographics such as region and size, the use of DRMS data allowed for the estimation of SCM incidence rates for cows treated with IMMA at dry off (SCM(+)). Because the treatment status of the cows in the DRMS data was not known, authors assumed all quarters of all cows to be treated with IMMA but not with a teat sealant. Treatment assumptions were made based on results from a National Animal Health Monitoring System survey in which 80.3% of surveyed dairy farmers stated they used IMMA on all cows at dry off while only 36.9% of producers used a teat sealant (USDA Animal and Plant Health Inspection Service, 2016).

Though CM incidence rates came from estimated values, they were similar to US-based studies (Godden et al., 2003, Pantoja et al., 2009a). By making incidence rate a stochastic variable by herd type and SCC group, a wide range of incidence rates were able to be accounted for, decreasing the risk of the incidence rates not being accurate. The use of incidence rates from Scherpenzeel et al. (2018) in the indexed values allowed for the estimation of CM(+), CM(-), and SCM(-) incidence rates for nine different SCC groups and more complete comparison between their results. Our model could be used in the future as more research is completed on ST or when the data from other dairy record-keeping systems are used as input variables in the analysis.

By using a weighted average of CM and SCM incidence rates, authors were able to compare a single incidence rate between DCT schemes. Both CM and SCM incidence rates were highest in NT and lowest in BT. Selective therapy and NT schemes had to have CM rates within 3% of the BT rate to become economically feasible. The difference in incidence rates became as small as 0.1% for ST to be feasible in the high SCC herd. These results suggest that for the simulated farms to use ST, CM incidence must be as low as when using BT.

Incidence rates of SCM could be within 25% of BT for ST and NT schemes to be economically feasible. The increase of incidence rates associated with SCM may be because SCM and CM simulations were run simultaneously. Running the simulations simultaneously could result in an iteration where the CM incidence rate associated with ST was low while the SCM mastitis incidence rate was high. The low CM incidence rate would have a greater impact on the total cost of the DCT therapy scheme to the farm because the cost of a case of CM was much higher than that of SCM. In future simulation models, the effect of CM and SCM incidence rates should be run separately.

Clinical and subclinical mastitis incidence was the main variable of interest in Huijps and Hogeveen (2007), Scherpenzeel et al. (2016), and Scherpenzeel et al. (2018). An additional goal of our study was to determine if cost variables would influence which treatment schemes were economically optimal. By examining multiple inputs, we were able to determine what other variables US farmers should consider when making DCT decisions.

Both Scherpenzeel et al. (2016) and Scherpenzeel et al. (2018) assumed the time to treat and labor wages were the same across both treatment types. However, in our study, the authors assumed there would be an increase in the associated with ST. The increase in time for ST would allow personnel to review data to determine which cows would need treatment, sort those cows, and perform dry off procedures. Authors also assumed that a farm manager outside of the milking parlor would complete ST, whereas BT would be administered by milkers in the milking parlor resulting in less time at a lower hourly wage. Authors found that BT cost more to farmers than ST only when unrealistic thresholds associated with labor were analyzed. Benefits of ST were not seen until labor wages reached over $55.00/hr, and the time of treatment for BT reached close to 0.50/hr per cow. Even at unrealistic values, NT never resulted in BT costing less. The lack of iterations in which NT cost less suggests that the cost of mastitis is greater than the labor savings associated with not treating cows at dry off.

The expense that led to the most variation in the optimal treatment decision was the cost of mastitis. When the cost of mastitis dropped below $250.00 per case, ST was, at times, an optimal DCT option. When calculating the cost of mastitis cases, milk price is the most influential variable (Shim et al., 2004, Huijps et al., 2008, Liang et al., 2017). For this reason, milk prices may affect DCT decisions. However, more research is needed to determine at what milk price decisions might be influenced.

Overall, Huijps and Hogeveen (2007), Scherpenzeel et al. (2016), Scherpenzeel et al. (2018) concluded that ST schemes cost less to dairy farmers than BT. Results presented in this analysis suggest that when modeled in a simulated US dairy system, BT costs less to dairy farmers than any ST scheme. Differences in the conclusion between our model and previous models are possibly due to the increased mastitis incidence that were derived from DRMS data and differences in model inputs. For example, Scherpenzeel et al. (2016) and Scherpenzeel et al. (2018) used calculated costs of CM of approximately $244 and $267 (US$)/case, respectively. Authors felt the use of $444/case presented by Rollin et al. (2015) would be a more accurate representation of a cost of CM associated with the dry period because their calculation was for the cost of CM within the first 30 days of a lactation. The estimation of the cost of SCM in our model was also higher than that used by Scherpenzeel et al. (2016) and Scherpenzeel et al. (2018) as both studies calculated the cost of SCM using milk losses associated with an increase in SCC at any point in the lactation. The use of milk loss associated with a first test day SCC presented by Nolan (2017) would be more representative of milk loss due to a SCM case around the time of calving.

CONCLUSIONS

The objectives of this study were to 1) determine the costs of BT and ST to a simulated US dairy herd, 2) determine if different selection criteria would lead to decreased costs of ST compared to BT, and 3) to determine how input costs and herd demographics would impact optimal DCT decisions. Overall, our simulations resulted in BT costing significantly less than NT and ST dry cow therapy schemes. In the simulated herds used in our study, farmers could save close to $9.75/cow per year by using BT compared to ST schemes. Results from our analysis suggest that when using ST schemes, the more cows that receive IMMA at dry off, the less cost the DCT scheme will have to the farm. The cost of mastitis should be considered when making DCT decisions. As mastitis costs decrease, ST became a more feasible therapy option. However, the variables that led to the greatest variability in DCT costs were CM and SCM incidence rates.

Table 3.1. The percent of cows[1] in each dry off groups (1 to 9) based on cow somatic cell count (SCC) (SCC*1,000 cells/mL) and parity on the last test day of the lactation in herds with differing SCC.

			Percent of cows in a herd		
Group	Dry off SCC (cells/mL*1000)[2]	Parity	Low SCC[3]	Average SCC[4]	High SCC[5]
1	0 to 50	1	23%	20%	18%
2	51 to 100	1	8%	8%	8%
3	101 to 150	1	3%	4%	4%
4	> 150	1	7%	9%	12%
5	0 to 50	2+	42%	35%	27%
6	51 to 100	2+	6%	8%	9%
7	101 to 150	2+	3%	4%	5%
8	151 to 250	2+	3%	4%	5%
9	> 250	2+	5%	8%	12%

[1]Percent of cows in each group were collected from Dairy Records Management Systems test day data from January 2015 to December 2017 with 7,020 herds included in the analysis.
[2]Dry off SCC = SCC at the last test of the cow's lactation
[3]Low SCC herds had SCC < 109,000 cells/mL
[4]Average SCC herd had SCC between 109,000 and 251,000 cells/mL
[5]High SCC herds had a SCC > 251,000 cells/mL

Table 3.2. Estimated incidence rates of clinical and subclinical mastitis[1], based on dry off groups (1 to 9), collected from Dairy Records Management Systems test-day data[2] from Holstein cows that calved between January 2015 and December 2017.

			Incidence rate in next lactation[3]			
			Clinical Mastitis		Subclinical Mastitis	
Group	Dry off SCC (cells/mL*1,000)	Parity	Treat (+)[4]	Treat (-)[5]	Treat (+)[6]	Treat (-)
1	0 to 50	1	11.53%	16.02%	9.05%	20.02%
2	51 to 100	1	14.97%	20.80%	11.75%	26.00%
3	101 to 150	1	17.48%	24.28%	13.72%	30.35%
4	> 150	1	25.32%	35.17%	19.87%	43.96%
5	0 to 50	2+	10.08%	14.81%	13.72%	22.70%
6	51 to 100	2+	11.77%	17.31%	16.03%	26.53%
7	101 to 150	2+	13.49%	19.82%	18.36%	30.38%
8	151 to 250	2+	15.56%	22.87%	21.18%	35.05%
9	> 250	2+	21.44%	31.51%	29.19%	48.31%

[1]Cows with a first test of the lactation with a SCC greater than 200,000 cells/ mL were considered to have subclinical mastitis

[2]Data from Dairy Records Management Systems were used to derive the incidence rate of subclinical mastitis in cows that received intramammary antibiotics at dry off

[3]Incidence rate of clinical and subclinical mastitis within the first 100 days of the next lactation

[4]Treat (+) = estimated incidence rates in the next lactation for cows that received intramammary antibiotics at dry off

[5]Treat (-) = estimated incidence rates in the next lactation for cows that did not receive intramammary antibiotics at dry off

[6]Incidence rates of the subclinical mastitis – Treat (+) group were derived from Dairy Records Management Systems data. These data were then used to create an estimate for the incidence rates of the remaining three groups by creating an index value from the incidence rates presented by Scherpenzeel et al. (2018). Index values were created using the following equation:

$$\mathrm{IIR} = \frac{\mathrm{SIR}}{\mathrm{SSCM(+)}} * \mathrm{DSCM(+)}$$

Where:
IIR = Index incidence rate
SIR = Incidence rate presented by Scherpenzeel et al. (2018)
SSCM(+) = Subclinical mastitis incidence rate for cows receiving intramammary antibiotics at dry off presented by Scherpenzeel et al. (2018)
DSCM(+) = Subclinical mastitis incidence rate for cows receiving intramammary antibiotics at dry off derived from Dairy Records Management Systems data

Table 3.3. Minimum, most likely, and maximum values for dry cow therapy costs variables entered into a PERT distribution to calculate dry cow therapy costs in a simulated dairy herd.

Variable	Min	Most Likely	Max
CM Cost ($/case)[1]	$244.00	$444.00	$644.00
SCM Cost ($/case)[2]	$5.65	$25.84	$56.21
ST Time (hrs)[3]	0.16	0.30	0.50
BT Time (hrs)[4]	0.08	0.16	0.25
ST Wages ($/hr)[5]	$26.50	$33.47	$40.50
BT Wages ($/hr)[6]	$10.50	$12.47	$14.50

[1]CM Cost = Cost of clinical mastitis ($/case)
[2]SCM Cost = Cost of subclinical mastitis ($/case)
[3]ST Time = Time of treatment using selective dry cow therapy (hrs)
[4]BT Time = Time of treatment using blanket dry cow therapy (hrs)
[5]ST Wage = Hourly wage paid to labor performing selective dry cow therapy ($/hr)
[6]BT Wage = Hourly wage paid to labor performing blanket dry cow therapy ($/hr)

Table 3.4. Minimum, most likely (ML), and maximum values used for estimated mastitis incidence rates based on mastitis type and treatment decision (+/-) entered into a PERT distribution as part of a simulation model to calculate dry cow therapy costs in a simulated dairy herd.

		Incidence rate in next lactation											
		Clinical Mastitis						Subclinical Mastitis					
		Treat (+)[1]			Treat (-)[2]			Treat (+)			Treat (-)		
Group	Dry off SCC	Min	ML	Max	Min	ML	Max	Min	ML	Max	Min	ML	Max
1	0–50	5.8%	11.5%	23.1%	8.0%	16.0%	32.0%	4.5%	9.1%	18.1%	10.0%	20.0%	40.0%
2	51–100	7.5%	15.0%	29.9%	10.4%	20.8%	41.6%	5.9%	11.8%	23.5%	13.0%	26.0%	52.0%
3	101–150	8.7%	17.5%	35.0%	12.1%	24.3%	48.6%	6.9%	13.7%	27.4%	15.2%	30.4%	60.7%
4	>150	12.7%	25.3%	50.6%	17.6%	35.2%	70.3%	9.9%	19.9%	39.7%	22.0%	44.0%	87.9%
5	0–50	5.0%	10.1%	20.2%	7.4%	14.8%	29.6%	6.9%	13.7%	27.4%	11.4%	22.7%	45.4%
6	51–100	5.9%	11.8%	23.5%	8.7%	17.3%	34.6%	8.0%	16.0%	32.1%	13.3%	26.5%	53.1%
7	101–150	6.7%	13.5%	27.0%	9.9%	19.8%	39.6%	9.2%	18.4%	36.7%	15.2%	30.4%	60.8%
8	151–250	7.8%	15.6%	31.1%	11.4%	22.9%	45.7%	10.6%	21.2%	42.4%	17.5%	35.1%	70.1%
9	>250	10.7%	21.4%	42.9%	15.8%	31.5%	63.0%	14.6%	29.2%	58.4%	24.2%	48.3%	96.6%

[1]Treat (+) = estimated mastitis incidence rates in the next lactation for cows that received intramammary antibiotics at dry off
[2]Treat (-) = estimated clinical mastitis incidence rates in the next lactation for cows that did not receive intramammary antibiotics at dry off

Table 3.5. Weighted average of clinical and subclinical mastitis incidence rates throughout the dry period and into the next lactation associated with herd somatic cell count and dry cow therapy treatment options.

	Clinical Mastitis			Subclinical Mastitis		
Treatment	Low[1]	Average[2]	High[3]	Low	Average	High
BT[4]	14.1%	15.0%	16.1%	15.4%	16.3%	17.5%
NT[5]	20.2%	21.5%	23.0%	28.4%	30.1%	32.2%
ST1[6]	18.9%	19.6%	20.4%	25.5%	26.1%	26.6%
ST2[7]	18.5%	19.0%	19.7%	24.5%	24.8%	25.2%
ST3[8]	17.7%	18.2%	18.9%	22.9%	23.0%	23.3%

[1]Low SCC herds had SCC < 109,000 cells/mL
[2]Average SCC herd had SCC between 109,000 and 251,000 cells/mL
[3]High SCC herds had a SCC > 251,000 cells/mL
[4]Blanket therapy = all cows received intramammary antibiotics at dry off
[5]No treatment = no cows received intramammary antibiotics at dry off
[6]ST1 = 1st parity cows with SCC > 150,000 cells/mL treated and 2+ parity cows with a SCC > 250,000 cells/mL treated
[7]ST2 = 1st parity cows with SCC > 100,000 cells/mL treated and 2+ parity cows with a SCC > 150,000 cells/mL treated
[8]ST3 = 1st parity cows with SCC > 50,000 cells/mL treated and 2+ parity cows with a SCC > 100,000 cells/mL treated

Table 3.6. Mean (± standard deviation) total costs of different dry cow therapy schemes used in simulated dairy herds with differing somatic cell counts.

Dry off scheme	Herd somatic cell count		
	Low[1]	Average[2]	High[3]
Blanket[4]	$10,637.35 ± 1,813.74[a]	$11,181.28 ± 1,877.44[a]	$11,851.88 ± 1,994.69[a]
No treatment[5]	$12,918.96 ± 2,717.66[b]	$13,687.99 ± 2,800.85[b]	$14,685.33 ± 2,965.71[b]
ST1[6]	$12,403.51 ± 2,549.09[c]	$12,961.54 ± 2,555.46[c]	$13,655.70 ± 2,603.78[c]
ST2[7]	$12,270.88 ± 2,494.69[c,d]	$12,785.76 ± 2,480.11[c,d]	$13,456.06 ± 2,519.17[c,d]
ST3[8]	$12,108.82 ± 2,406.26[d]	$12,608.58 ± 2,377.02[d]	$13,260.96 ± 2,400.46[d]

[1]Low SCC herd had a SCC of 109,000 cells/ml
[2]Average SCC herd had a SCC of 251,000 cells/mL
[3]High SCC herd had a SCC of 393,000 cells/mL
[4]Blanket therapy = all cows received intramammary antibiotics at dry off
[5]No treatment = no cows received intramammary antibiotics at dry off
[6]ST1 = 1st parity cows with SCC > 150,000 cells/mL treated and 2+ parity cows with an SCC > 250,000 cells/mL treated
[7]ST2 = 1st parity cows with SCC > 100,000 cells/mL treated and 2+ parity cows with an SCC > 150,000 cells/mL treated
[8]ST3 = 1st parity cows with SCC > 50,000 cells/mL treated and 2+ parity cows with an SCC > 100,000 cells/mL treated
[a-d] Means within a column with a different superscript are significantly different (*P* < 0.05)

Table 3.7. Mean (± standard deviation) differences in dry cow therapy costs when using different dry cow therapy schemes in simulated dairy herds with differing somatic cell counts.

	Herd somatic cell count		
	Low[1]	Average[2]	High[3]
Blanket[4] vs No Treatment[5]	$2,281.61 ± 1,859.34	$2,519.75 ± 1,816.13	$2,833.46 ± 1,886.88
Blanket vs ST1[6]	$1,766.16 ± 1,669.87	$1,793.30 ± 1,490.21	$1,803.82 ± 1,306.60
Blanket vs ST2[7]	$1,633.53 ± 1,625.79	$1,617.52 ± 1,422.09	$1,604.18 ± 1,222.18
Blanket vs ST3[8]	$1,471.47 ± 1,546.47	$1,440.34 ± 1,343.97	$1,409.08 ± 1,122.04

[1]Low SCC herd had a SCC of 109,000 cells/ml
[2]Average SCC herd had a SCC of 251,000 cells/mL
[3]High SCC herd had a SCC of 393,000 cells/mL
[4]Blanket therapy = all cows received intramammary antibiotics at dry off
[5]No treatment = no cows received intramammary antibiotics at dry off
[6]ST1 = 1st parity cows with SCC > 150,000 cells/mL treated and 2+ parity cows with an SCC > 250,000 cells/mL treated
[7]ST2 = 1st parity cows with SCC > 100,000 cells/mL treated and 2+ parity cows with an SCC > 150,000 cells/mL treated
[8]ST3 = 1st parity cows with SCC > 50,000 cells/mL treated and 2+ parity cows with an SCC > 100,000 cells/mL treated

Table 3.8. The frequency of iterations and the value of dry cow therapy cost variables in which different dry cow therapy schemes cost less than blanket dry cow therapy in a simulated low somatic cell count herd[1].

			Dry cow therapy scheme comparisons			
Variable	Variable Distribution	Frequency[2] and value	BT[3] vs NT[4]	BT vs ST1[5]	BT vs ST2[6]	BT vs ST3[7]
CM Cost ($/case)[8]	$111.00 to $777.00	Frequency	1.3%	1.6%	1.3%	0.5%
		Value[12]	$186.19	$193.68	$186.19	$165.56
BT Wages ($/hr)[9]	$10.50 to $90.00	Frequency	0.0%	1.2%	4.1%	9.7%
		Value[13]	N/A	$81.10	$76.02	$70.52
BT Time (hrs)[10]	0.08 to 0.50 hrs	Frequency	0.0%	6.8%	11.9%	19.4%
		Value[14]	N/A	0.39	0.36	0.34
Mastitis IR[11]	Half to Double IR	Frequency	5.4%	8.2%	10.1%	12.2%
Clinical mastitis		Value[15]	2.1%	1.7%	1.4%	1.0%
Subclinical mastitis		Value[15]	21.8%	25.4%	24.9%	22.0%

[1]Low SCC herd had a SCC of 109,000 cells/ml
[2]Frequency = the percent of iterations in which compared dry cow therapy scheme cost less than blanket dry cow therapy
[3]Blanket therapy = all cows received intramammary antibiotics at dry off
[4]No treatment = no cows received intramammary antibiotics at dry off
[5]ST1 = 1st parity cows with SCC > 150,000 cells/mL treated and 2+ parity cows with an SCC > 250,000 cells/mL treated
[6]ST2 = 1st parity cows with SCC > 100,000 cells/mL treated and 2+ parity cows with an SCC > 150,000 cells/mL treated
[7]ST3 = 1st parity cows with SCC > 50,000 cells/mL treated and 2+ parity cows with an SCC > 100,000 cells/mL treated
[8]CM Cost = The cost of clinical mastitis ($/case)
[9]BT Time = Time of treatment using blanket dry cow therapy (hrs)
[10]BT Wage = Hourly wage paid to labor performing blanket dry cow therapy ($/hr)
[11]Mastitis IR = Population incidence rate of clinical and subclinical mastitis
[12]Value = the maximum CM cost in which the respective therapy option would cost less than BT
[13]Value = the maximum wage paid to BT labor in which the respective therapy option would cost less than BT
[14]Value = the maximum time to treat when using BT in which the respective therapy option would cost less than BT
[15]Value = the maximum difference in CM or SCM incidence rate, comparing the respective therapy option to BT, in which the respective therapy would cost less than BT

Table 3.9. The frequency of iterations and the value of dry cow therapy cost variables in which different dry cow therapy schemes cost less than blanket dry cow therapy in a simulated average somatic cell count herd[1].

			Dry cow therapy scheme comparisons			
Variable	Variable Distribution	Frequency[2] and value	BT[3] vs NT[4]	BT vs ST1[5]	BT vs ST2[6]	BT vs ST3[7]
CM Cost ($/case)[8]	$111.00 to $777.00	Frequency	0.8%	0.4%	0.6%	0.1%
		Value[12]	$173.84	$178.28	$166.53	$123.30
BT Wages ($/hr)[9]	$10.50 to $90.00	Frequency	0.0%	1.0%	4.0%	10.0%
		Value[13]	N/A	$83.70	$76.54	$70.24
BT Time (hrs)[10]	0.08 to 0.50 hrs	Frequency	0.0%	19.3%	29.8%	38.4%
		Value[14]	N/A	0.40	0.37	0.34
Mastitis IR[11]	Half to Double IR	Frequency	2.8%	4.9%	6.6%	8.3%
Clinical mastitis		Value[15]	1.8%	1.5%	1.2%	0.7%
Subclinical mastitis		Value[15]	21.8%	17.6%	22.7%	14.4%

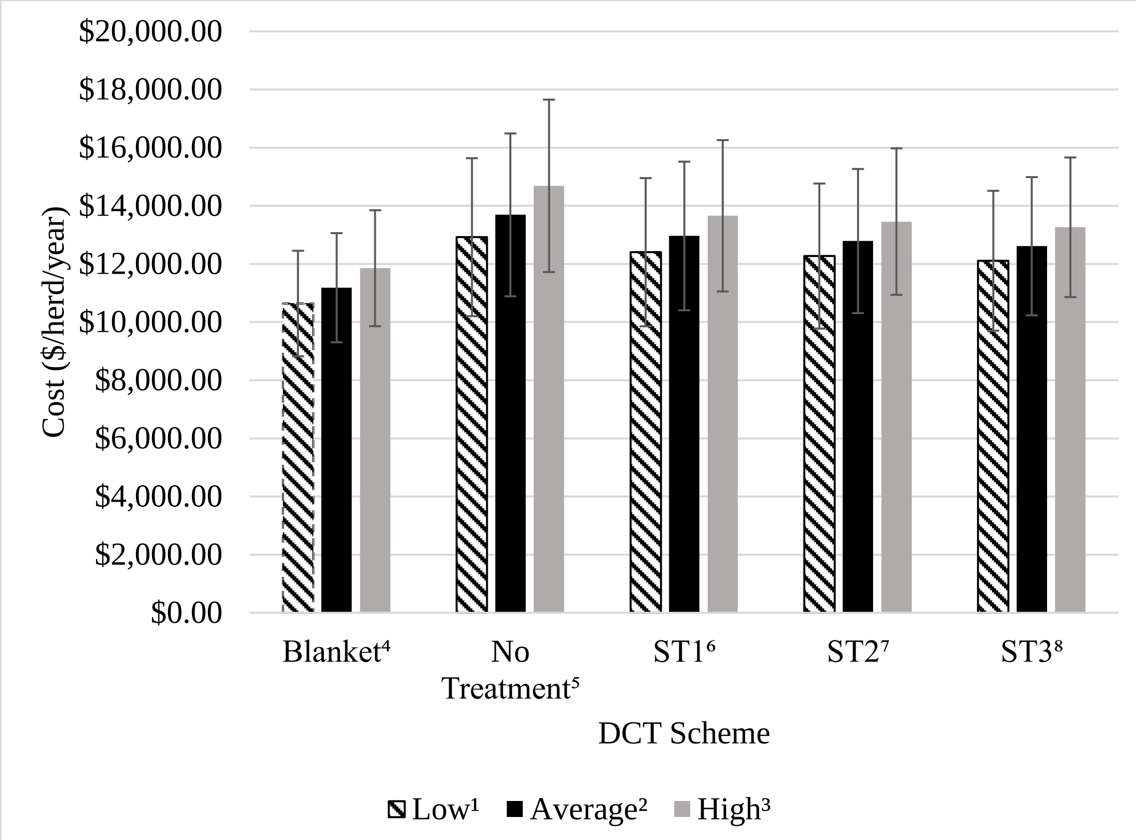
[1]Average SCC herd had a SCC of 251,000 cells/ml
[2]Frequency = the percent of iterations in which compared dry cow therapy scheme cost less than blanket dry cow therapy
[3]Blanket therapy = all cows received intramammary antibiotics at dry off
[4]No treatment = no cows received intramammary antibiotics at dry off
[5]ST1 = 1st parity cows with SCC > 150,000 cells/mL treated and 2+ parity cows with an SCC > 250,000 cells/mL treated
[6]ST2 = 1st parity cows with SCC > 100,000 cells/mL treated and 2+ parity cows with an SCC > 150,000 cells/mL treated
[7]ST3 = 1st parity cows with SCC > 50,000 cells/mL treated and 2+ parity cows with an SCC > 100,000 cells/mL treated
[8]CM Cost = The cost of clinical mastitis ($/case)
[9]BT Time = Time of treatment using blanket dry cow therapy (hrs)
[10]BT Wage = Hourly wage paid to labor performing blanket dry cow therapy ($/hr)
[11]Mastitis IR = Population incidence rate of clinical and subclinical mastitis
[12]Value = the maximum CM cost in which the respective therapy option would cost less than BT
[13]Value = the maximum wage paid to BT labor in which the respective therapy option would cost less than BT
[14]Value = the maximum time to treat when using BT in which the respective therapy option would cost less than BT
[15]Value = the maximum difference in CM or SCM incidence rate, comparing the respective therapy option to BT, in which the respective therapy would cost less than BT

Table 3.10. The frequency of iterations and the value of dry cow therapy cost variables in which different dry cow therapy schemes cost less than blanket dry cow therapy in a simulated high somatic cell count herd[1].

			Dry cow therapy scheme comparisons			
Variable	Variable Distribution	Frequency[2] and value	BT[3] vs NT[4]	BT vs ST1[5]	BT vs ST2[6]	BT vs ST3[7]
CM Cost ($/case)[8]	$111.00 to $777.00	Frequency	0.4%	0.3%	0.1%	0.0%
		Value[12]	$158.68	$155.30	$123.30	N/A
BT Wages ($/hr)[9]	$10.50 to $90.00	Frequency	0.0%	1.0%	3.8%	10.8%
		Value[13]	N/A	$84.06	$76.41	$69.65
BT Time (hrs)[10]	0.08 to 0.50 hrs	Frequency	0.0%	0.4%	3.8%	10.8%
		Value[14]	N/A	0.40	0.37	0.33
Mastitis IR[11]	Half to Double IR	Frequency	2.4%	3.5%	4.1%	4.7%
Clinical mastitis		Value[15]	2.0%	1.1%	0.7%	0.1%
Subclinical mastitis		Value[15]	20.4%	16.0%	20.0%	12.5%

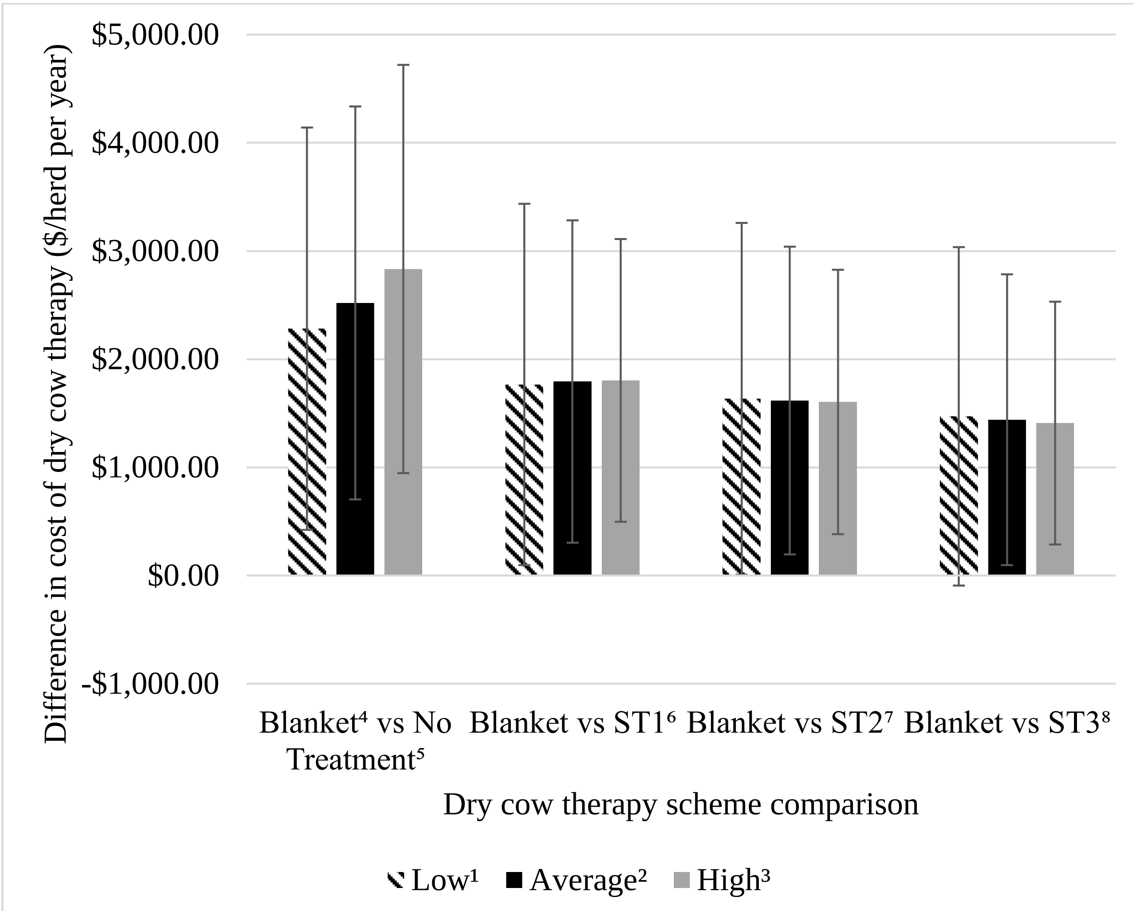
[1]High SCC herd had a SCC of 393,000 cells/ml
[2]Frequency = the percent of iterations in which compared dry cow therapy scheme cost less than blanket dry cow therapy
[3]Blanket therapy = all cows received intramammary antibiotics at dry off
[4]No treatment = no cows received intramammary antibiotics at dry off
[5]ST1 = 1st parity cows with SCC > 150,000 cells/mL treated and 2+ parity cows with an SCC > 250,000 cells/mL treated
[6]ST2 = 1st parity cows with SCC > 100,000 cells/mL treated and 2+ parity cows with an SCC > 150,000 cells/mL treated
[7]ST3 = 1st parity cows with SCC > 50,000 cells/mL treated and 2+ parity cows with an SCC > 100,000 cells/mL treated
[8]CM Cost = The cost of clinical mastitis ($/case)
[9]BT Time = Time of treatment using blanket dry cow therapy (hrs)
[10]BT Wage = Hourly wage paid to labor performing blanket dry cow therapy ($/hr)
[11]Mastitis IR = Population incidence rate of clinical and subclinical mastitis
[12]Value = the maximum CM cost in which the respective therapy option would cost less than BT
[13]Value = the maximum wage paid to BT labor in which the respective therapy option would cost less than BT
[14]Value = the maximum time to treat when using BT in which the respective therapy option would cost less than BT
[15]Value = the maximum difference in CM or SCM incidence rate, comparing the respective therapy option to BT, in which the respective therapy would cost less than BT

Figure 3.1. Mean (± standard deviation) costs of different dry cow therapy schemes used in simulated dairy herds with differing somatic cell counts.



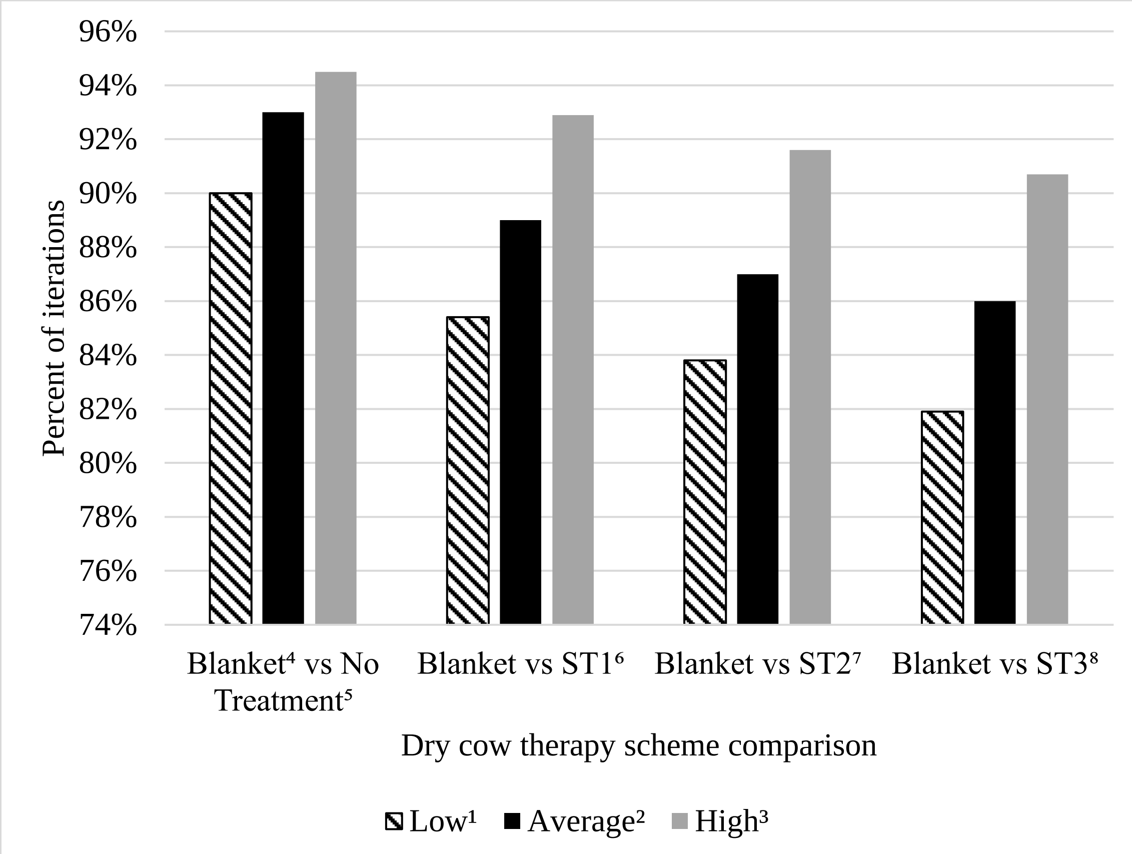
[1]Low SCC herd had a SCC of 109,000 cells/ml
[2]Average SCC herd had a SCC of 251,000 cells/mL
[3]High SCC herd had a SCC of 393,000 cells/mL
[4]Blanket therapy = all cows received intramammary antibiotics at dry off
[5]No treatment = no cows received intramammary antibiotics at dry off
[6]ST1 = 1st parity cows with SCC > 150,000 cells/mL and 2+ parity cows with an SCC > 250,000 cells/mL treated with an intramammary antibiotic at dry off
[7]ST2 = 1st parity cows with SCC > 100,000 cells/mL and 2+ parity cows with an SCC > 150,000 cells/mL treated with an intramammary antibiotic at dry off
[8]ST3 = 1st parity cows with SCC > 50,000 cells/mL and 2+ parity cows with an SCC > 100,000 cells/mL treated with an intramammary antibiotic at dry off
[a-d] Means within same bar fill with a different superscript are significantly different ($P < 0.05$)

Figure 3.2. Mean (± standard deviation) differences in dry cow therapy costs when using different dry cow therapy schemes in simulated dairy herds with differing somatic cell counts.



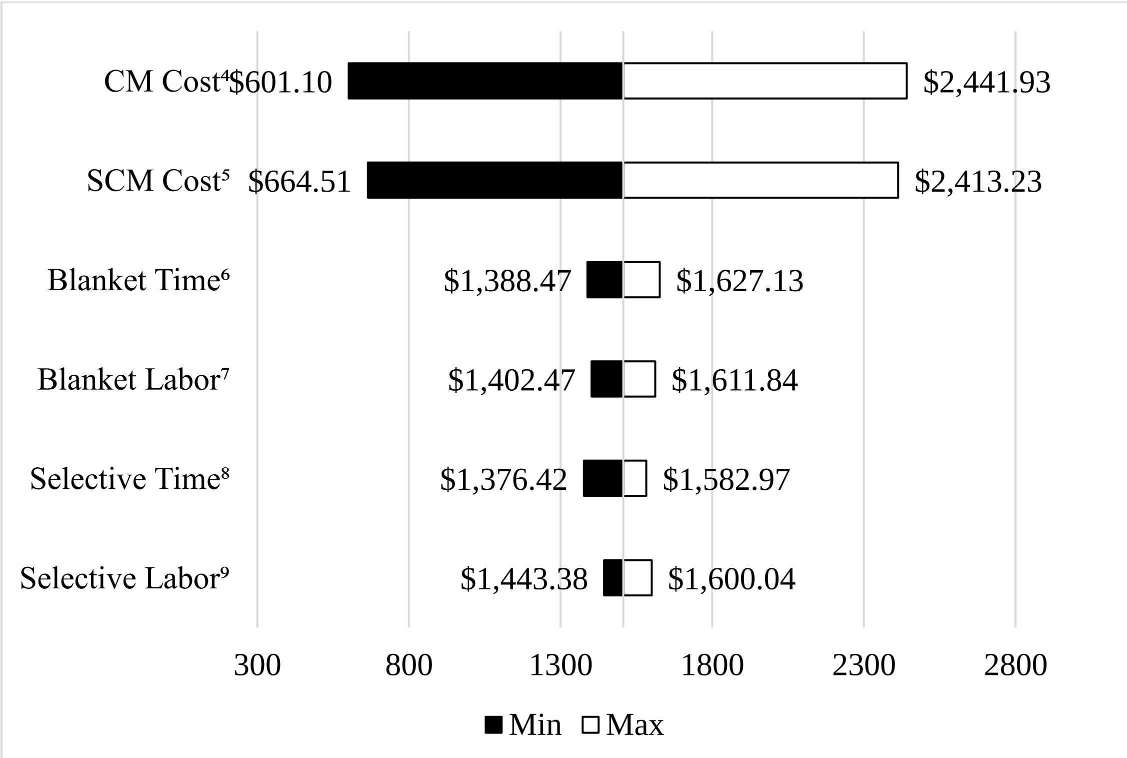
[1]Low SCC herd had a SCC of 109,000 cells/ml
[2]Average SCC herd had a SCC of 251,000 cells/mL
[3]High SCC herd had a SCC of 393,000 cells/mL
[4]Blanket therapy = all cows received intramammary antibiotics at dry off
[5]No treatment = no cows received intramammary antibiotics at dry off
[6]ST1 = 1st parity cows with SCC > 150,000 cells/mL and 2+ parity cows with an SCC > 250,000 cells/mL treated with an intramammary antibiotic at dry off
[7]ST2 = 1st parity cows with SCC > 100,000 cells/mL and 2+ parity cows with an SCC > 150,000 cells/mL treated with an intramammary antibiotic at dry off
[8]ST3 = 1st parity cows with SCC > 50,000 cells/mL and 2+ parity cows with an SCC > 100,000 cells/mL treated with an intramammary antibiotic at dry off

Figure 3.3. Frequency of a 1,000 iteration simulation in which blanket dry cow therapy cost less than different dry cow therapy schemes in simulated dairy herds.



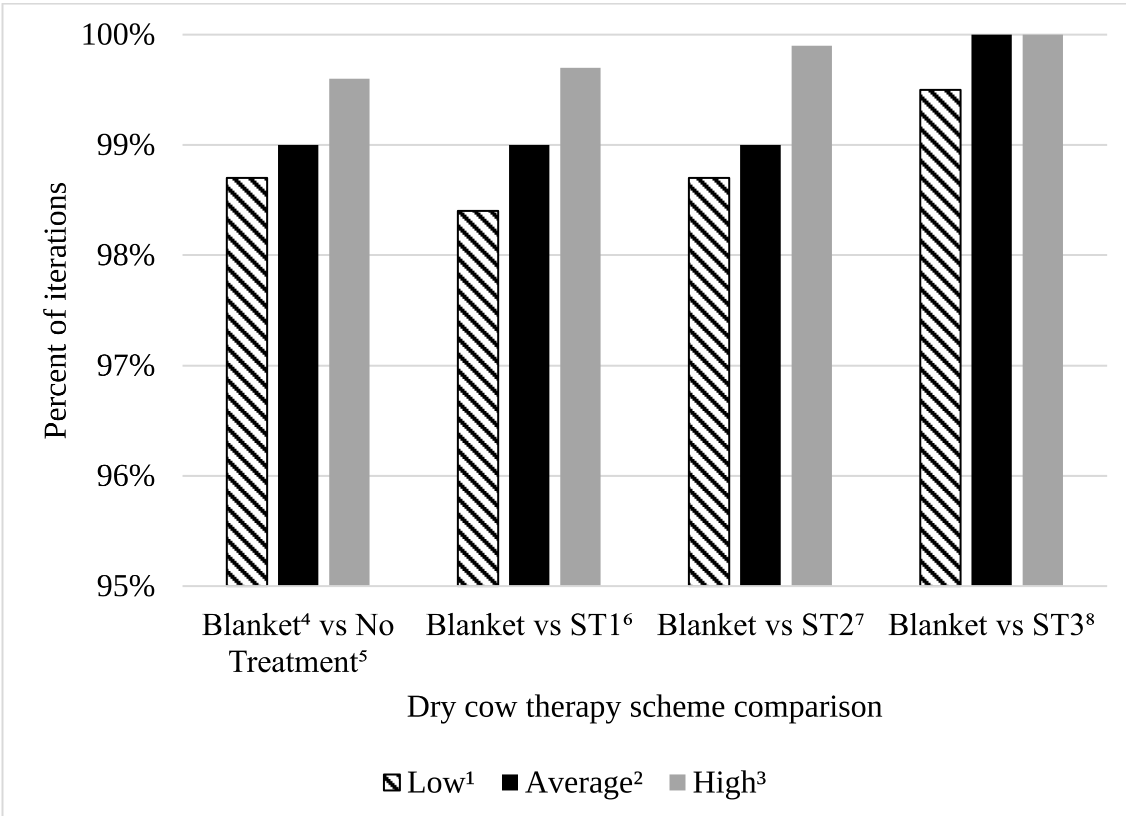
[1]Low SCC herd had a SCC of 109,000 cells/ml
[2]Average SCC herd had a SCC of 251,000 cells/mL
[3]High SCC herd had a SCC of 393,000 cells/mL
[4]Blanket therapy = all cows received intramammary antibiotics at dry off
[5]No treatment = no cows received intramammary antibiotics at dry off
[6]ST1 = 1st parity cows with SCC > 150,000 cells/mL and 2+ parity cows with an SCC > 250,000 cells/mL treated with an intramammary antibiotic at dry off
[7]ST2 = 1st parity cows with SCC > 100,000 cells/mL and 2+ parity cows with an SCC > 150,000 cells/mL treated with an intramammary antibiotic at dry off
[8]ST3 = 1st parity cows with SCC > 50,000 cells/mL and 2+ parity cows with an SCC > 100,000 cells/mL treated with an intramammary antibiotic at dry off

Figure 3.4. A tornado graph depicting the range of the difference in the total cost between blanket[1] and selective dry cow therapy[2] schemes associated with the change of cost variables for a simulated dairy herd with a low SCC (109,000 cells/mL). The average cost difference was $1,506.64[3].



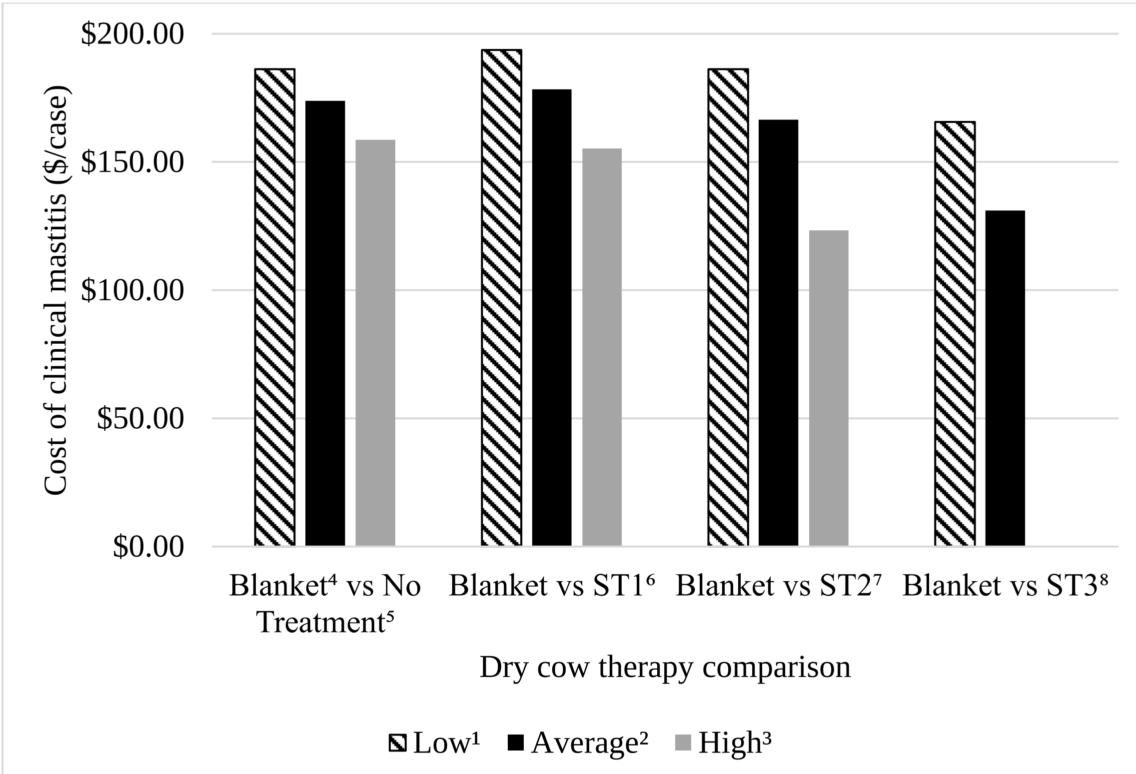
[1]Blanket dry cow therapy = all cows treated with intramammary antibiotic
[2]Selective dry cow therapy scheme = treating only 1st parity cows with SCC > 150,000 cells/mL and 2+ parity cows with an SCC > 250,000 cells/mL
[3]Value is the average difference in total cost of blanket dry cow and selective dry cow therapy scheme.
[4]CM Cost = Cost of clinical mastitis ($/case)
[5]SCM Cost = Cost of subclinical mastitis ($/case)
[6]Blanket Time = Time of treatment using blanket dry cow therapy (hrs)
[7]Blanket Labor = Hourly wage paid to labor performing blanket dry cow therapy ($/hr)
[8]Selective Time = Time of treatment using selective dry cow therapy (hrs)
[9]Selective Labor = Hourly wage paid to labor performing selective dry cow therapy ($/hr)

Figure 3.5. Frequency of a 1,000 iteration simulation in which blanket dry cow therapy cost less than different dry cow therapy schemes in simulated dairy herds when comparing clinical mastitis case cost that ranged from $111.00 to $777.00/case.



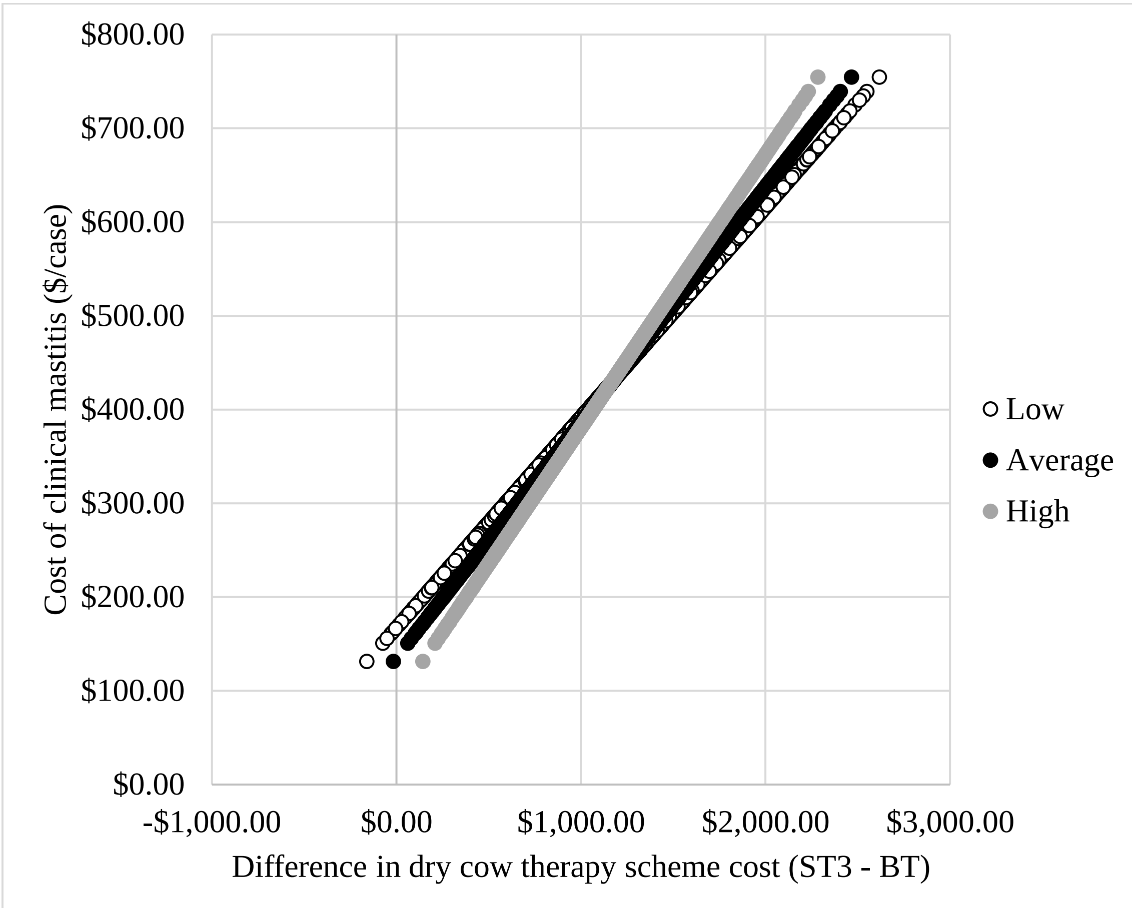
[1]Low SCC herd had a SCC of 109,000 cells/ml
[2]Average SCC herd had a SCC of 251,000 cells/mL
[3]High SCC herd had a SCC of 393,000 cells/mL
[4]Blanket therapy = all cows received intramammary antibiotics at dry off
[5]No treatment = no cows received intramammary antibiotics at dry off
[6]ST1 = 1st parity cows with SCC > 150,000 cells/mL and 2+ parity cows with an SCC > 250,000 cells/mL treated with an intramammary antibiotic at dry off
[7]ST2 = 1st parity cows with SCC > 100,000 cells/mL and 2+ parity cows with an SCC > 150,000 cells/mL treated with an intramammary antibiotic at dry off
[8]ST3 = 1st parity cows with SCC > 50,000 cells/mL and 2+ parity cows with an SCC > 100,000 cells/mL treated with an intramammary antibiotic at dry off

Figure 3.6. The maximum cost of a case of clinical mastitis in which a compared dry cow therapy scheme cost less than blanket dry cow therapy in simulated dairy herds.



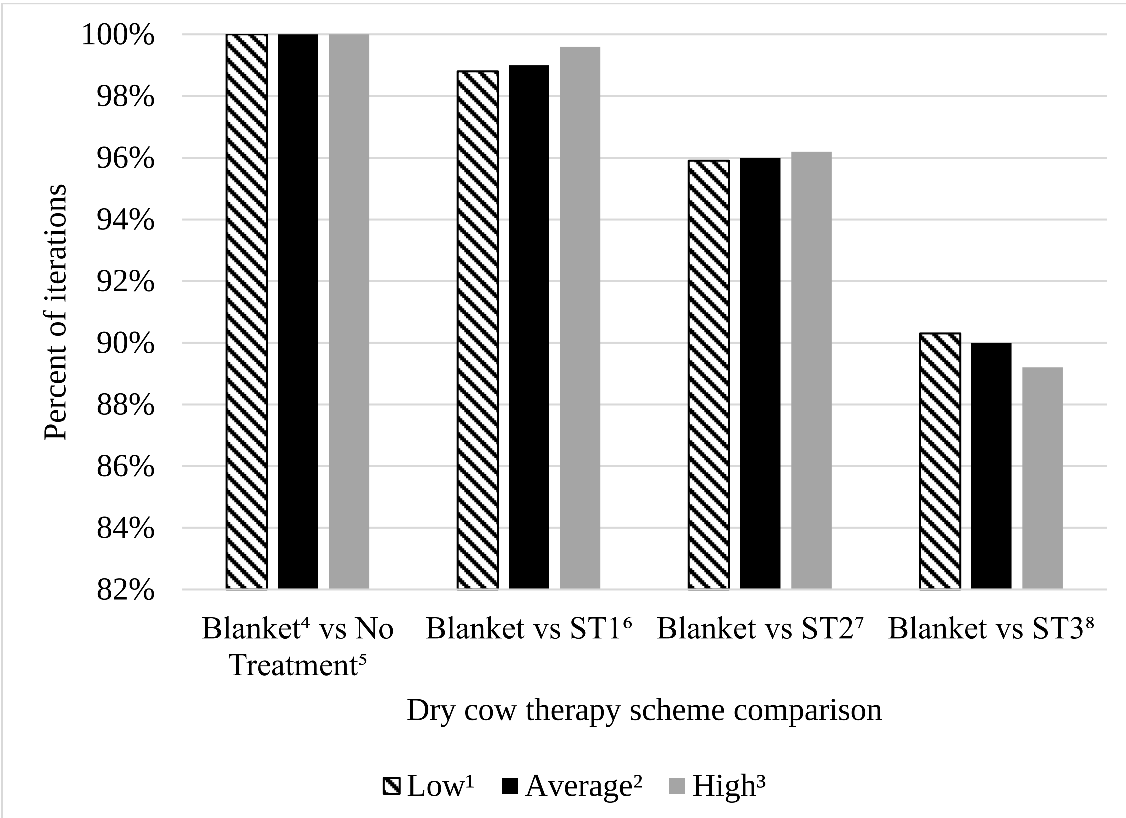
[1]Low SCC herd had a SCC of 109,000 cells/ml
[2]Average SCC herd had a SCC of 251,000 cells/mL
[3]High SCC herd had a SCC of 393,000 cells/mL
[4]Blanket therapy = all cows received intramammary antibiotics at dry off
[5]No treatment = no cows received intramammary antibiotics at dry off
[6]ST1 = 1st parity cows with SCC > 150,000 cells/mL and 2+ parity cows with an SCC > 250,000 cells/mL treated with an intramammary antibiotic at dry off
[7]ST2 = 1st parity cows with SCC > 100,000 cells/mL and 2+ parity cows with an SCC > 150,000 cells/mL treated with an intramammary antibiotic at dry off
[8]ST3 = 1st parity cows with SCC > 50,000 cells/mL and 2+ parity cows with an SCC > 100,000 cells/mL treated with an intramammary antibiotic at dry off.
No cost of ST3 associated with the high herd because the total cost of ST3 was never lower than Blanket therapy when the cost of CM changed.

Figure 3.7. Changes in the difference between the cost of blanket dry cow therapy[1] and a selective dry cow therapy[2] (ST3) scheme as the cost of clinical mastitis changes for simulated dairy herds with low[3], average[4], and high[5] somatic cell counts.



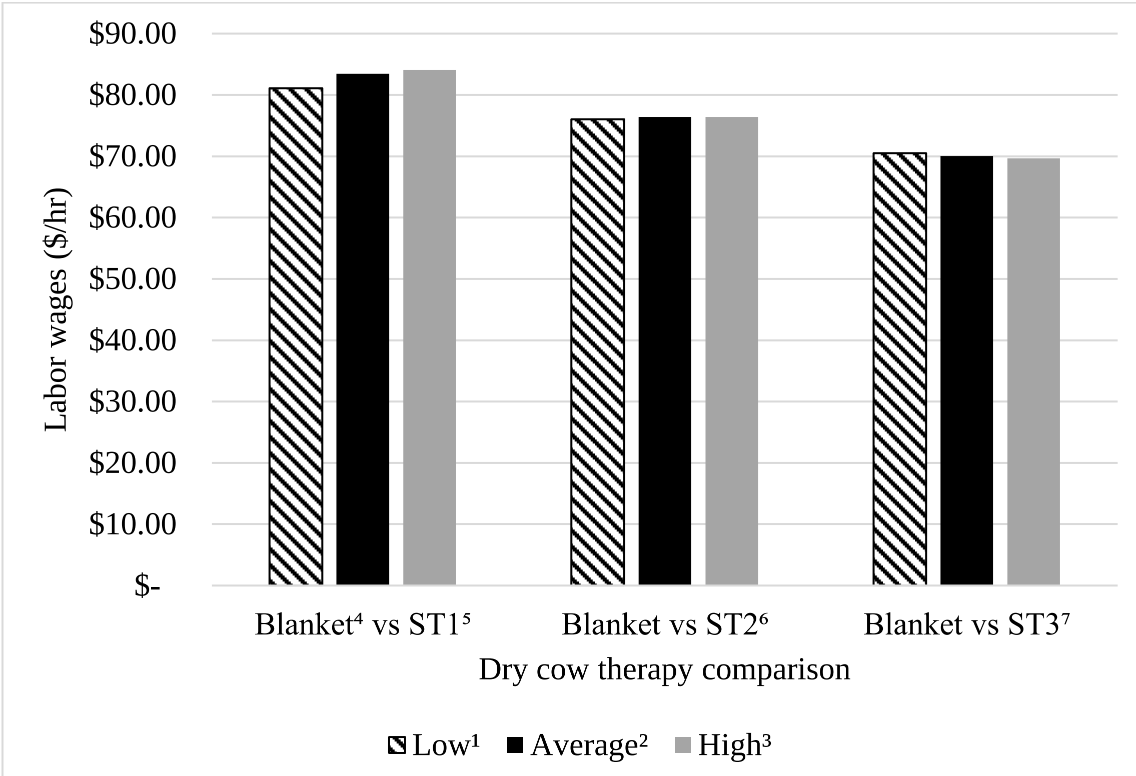
[1]Blanket dry cow therapy = all cows treated with intramammary antibiotic
[2]Selective dry cow therapy scheme = 1st parity cows with SCC > 50,000 cells/mL and 2+ parity cows with an SCC > 100,000 cells/mL treated with an intramammary antibiotic at dry off. Defined as ST3 in text of paper.
[3]Low SCC herd had a SCC of 109,000 cells/ml
[4]Average SCC herd had a SCC of 251,000 cells/mL
[5]High SCC herd had a SCC of 393,000 cells/mL

Figure 3.8. Frequency of a 1,000 iteration simulation in which blanket dry cow therapy cost less than different dry cow therapy schemes in simulated dairy herds when comparing wages paid for labor ($10.50 to $90.00/hr) using a blanket dry cow therapy scheme.



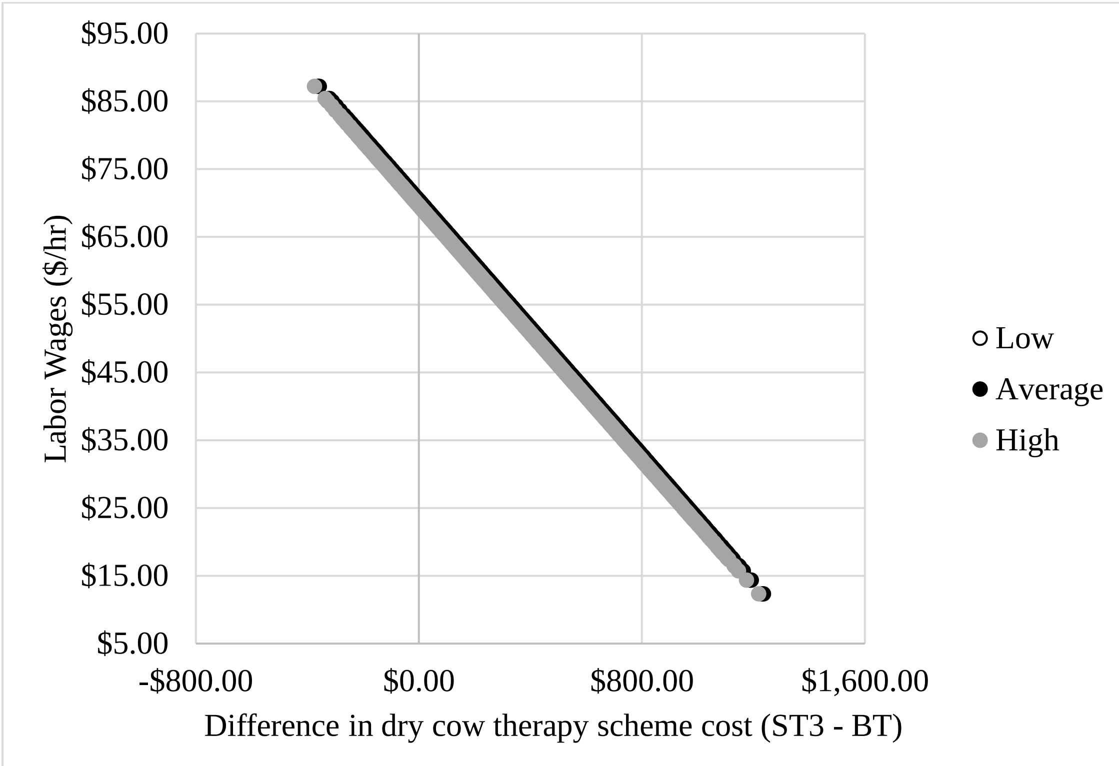
[1]Low SCC herd had a SCC of 109,000 cells/ml
[2]Average SCC herd had a SCC of 251,000 cells/mL
[3]High SCC herd had a SCC of 393,000 cells/mL
[4]Blanket therapy = all cows received intramammary antibiotics at dry off
[5]No treatment = no cows received intramammary antibiotics at dry off
[6]ST1 = 1st parity cows with SCC > 150,000 cells/mL and 2+ parity cows with an SCC > 250,000 cells/mL treated with an intramammary antibiotic at dry off
[7]ST2 = 1st parity cows with SCC > 100,000 cells/mL and 2+ parity cows with an SCC > 150,000 cells/mL treated with an intramammary antibiotic at dry off
[8]ST3 = 1st parity cows with SCC > 50,000 cells/mL and 2+ parity cows with an SCC > 100,000 cells/mL treated with an intramammary antibiotic at dry off

Figure 3.9. The minimum wage paid to labor performing blanket dry cow therapy in which a compared dry cow therapy scheme cost less than blanket dry cow therapy in simulated dairy herds.



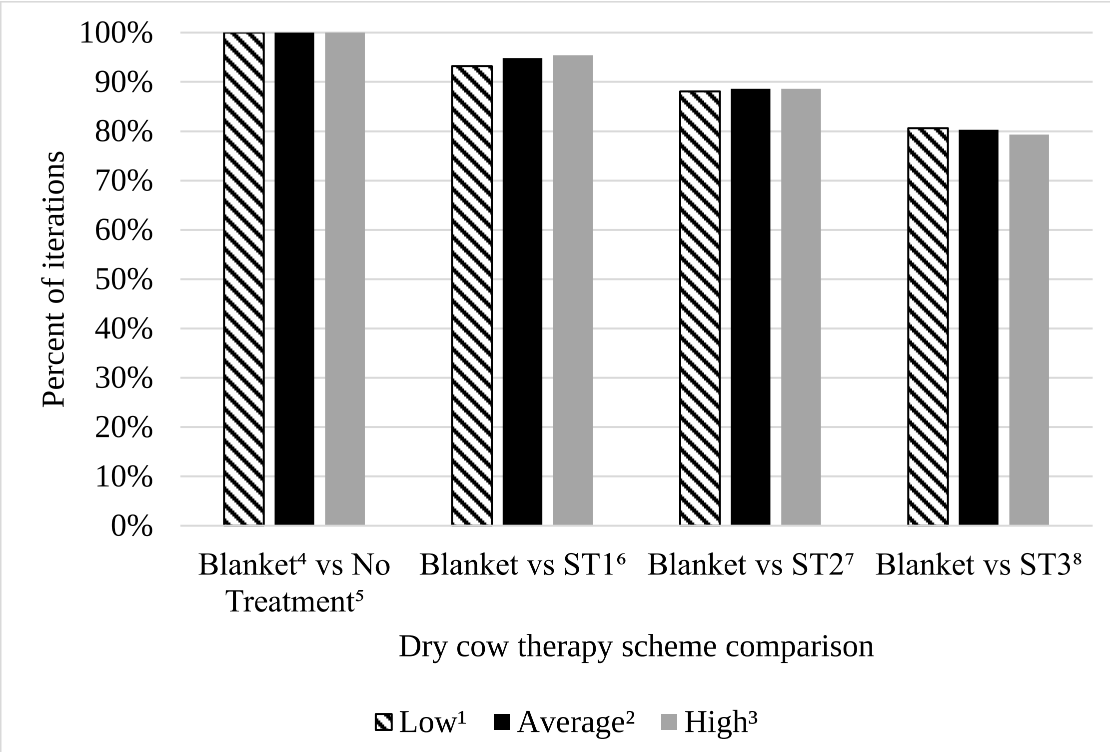
[1]Low SCC herd had a SCC of 109,000 cells/ml
[2]Average SCC herd had a SCC of 251,000 cells/mL
[3]High SCC herd had a SCC of 393,000 cells/mL
[4]Blanket therapy = all cows received intramammary antibiotics at dry off
[5]ST1 = 1st parity cows with SCC > 150,000 cells/mL and 2+ parity cows with an SCC > 250,000 cells/mL treated with an intramammary antibiotic at dry off
[6]ST2 = 1st parity cows with SCC > 100,000 cells/mL and 2+ parity cows with an SCC > 150,000 cells/mL treated with an intramammary antibiotic at dry off
[7]ST3 = 1st parity cows with SCC > 50,000 cells/mL and 2+ parity cows with an SCC > 100,000 cells/mL treated with an intramammary antibiotic at dry off

Figure 3.10. Changes in the difference between the cost of blanket dry cow therapy[1] and a selective dry cow therapy[2] (ST3) scheme as the associated labor wage changes for simulated dairy herds with low[3], average[4], and high[5] somatic cell counts.



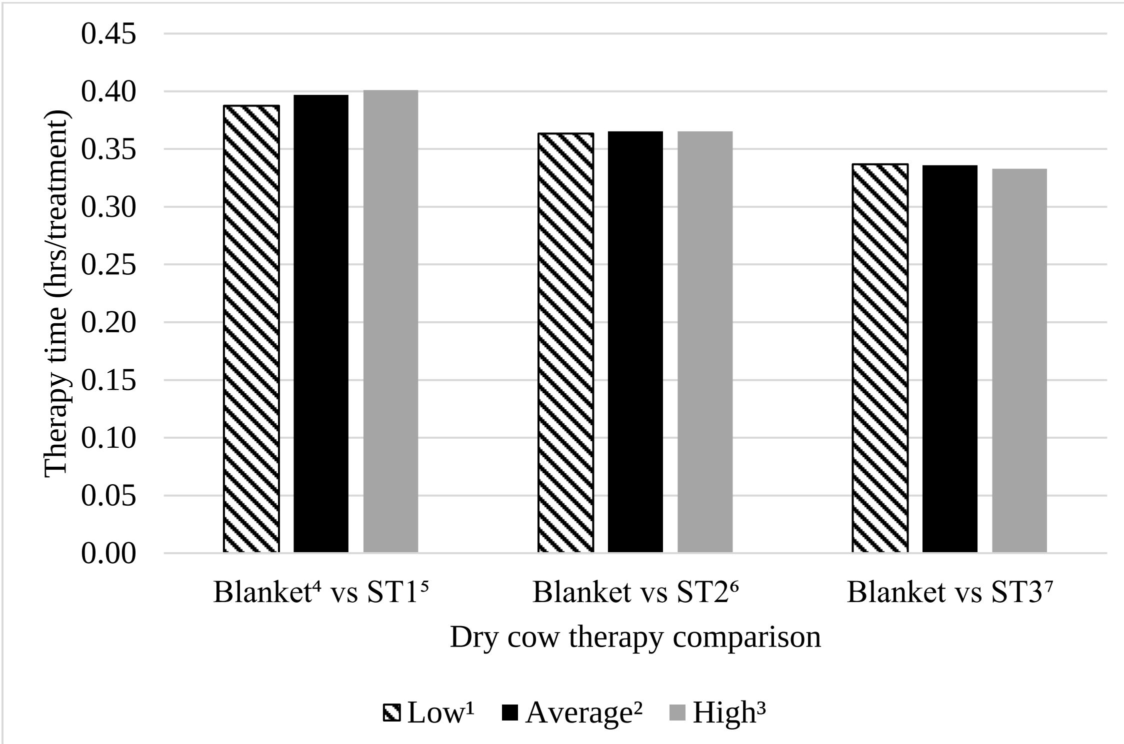
[1]Blanket dry cow therapy = all cows treated with intramammary antibiotic
[2]Selective dry cow therapy scheme = 1st parity cows with SCC > 50,000 cells/mL and 2+ parity cows with an SCC > 100,000 cells/mL treated with an intramammary antibiotic at dry off. Defined as ST3 in text of paper.
[3]Low SCC herd had a SCC of 109,000 cells/ml
[4]Average SCC herd had a SCC of 251,000 cells/mL
[5]High SCC herd had a SCC of 393,000 cells/mL

Figure 3.11. Frequency of a 1,000 iteration simulation in which blanket dry cow therapy cost less than different dry cow therapy schemes in simulated dairy herds when comparing time (0.08 to 0.50 hrs) of treatment for labor .



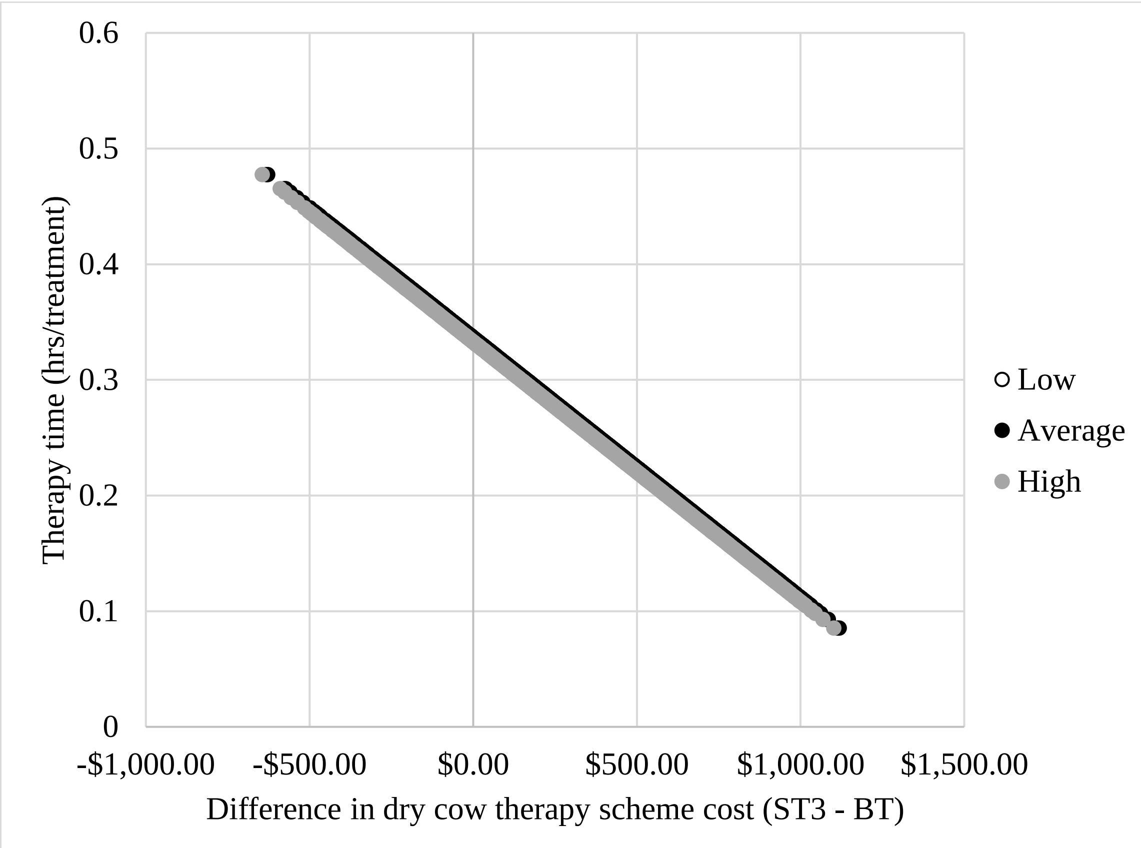
[1]Low SCC herd had a SCC of 109,000 cells/ml
[2]Average SCC herd had a SCC of 251,000 cells/mL
[3]High SCC herd had a SCC of 393,000 cells/mL
[4]Blanket therapy = all cows received intramammary antibiotics at dry off
[5]No treatment = no cows received intramammary antibiotics at dry off
[6]ST1 = 1st parity cows with SCC > 150,000 cells/mL and 2+ parity cows with an SCC > 250,000 cells/mL treated with an intramammary antibiotic at dry off
[7]ST2 = 1st parity cows with SCC > 100,000 cells/mL and 2+ parity cows with an SCC > 150,000 cells/mL treated with an intramammary antibiotic at dry off
[8]ST3 = 1st parity cows with SCC > 50,000 cells/mL and 2+ parity cows with an SCC > 100,000 cells/mL treated with an intramammary antibiotic at dry off

Figure 3.12. The minimum time for performing blanket dry cow therapy in which a compared dry cow therapy scheme cost less than blanket dry cow therapy in simulated dairy herds.



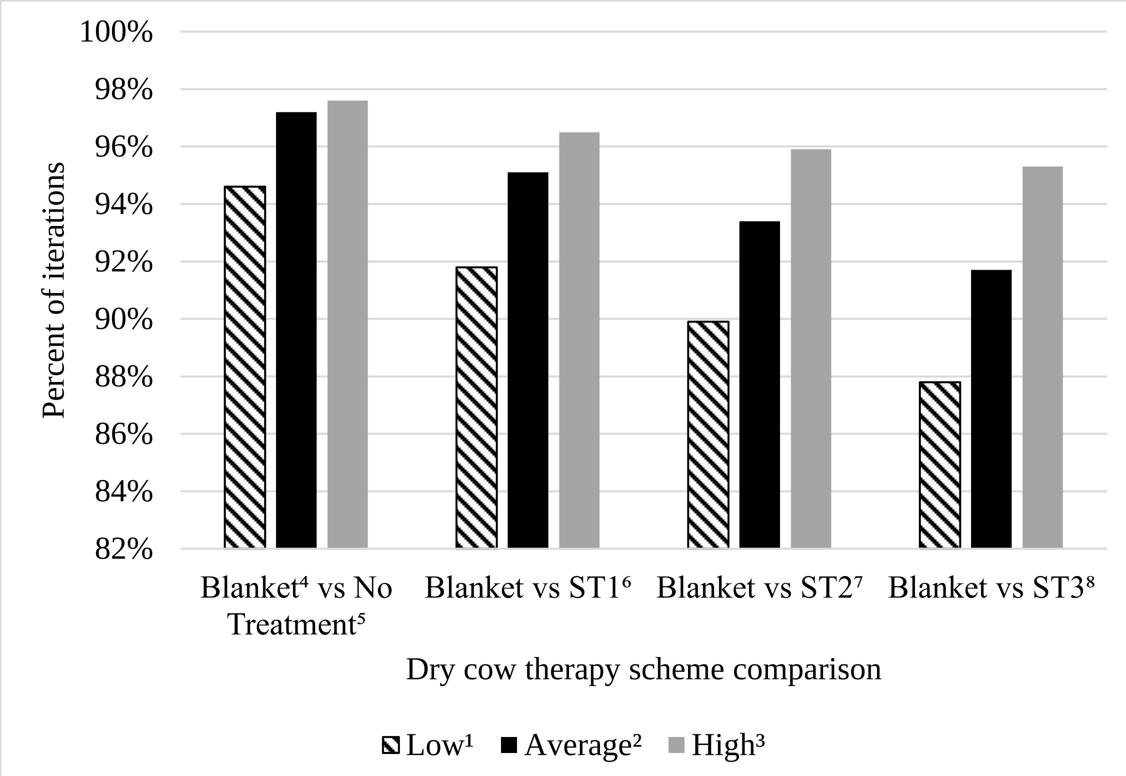
[1]Low SCC herd had a SCC of 109,000 cells/ml
[2]Average SCC herd had a SCC of 251,000 cells/mL
[3]High SCC herd had a SCC of 393,000 cells/mL
[4]Blanket therapy = all cows received intramammary antibiotics at dry off
[5]ST1 = 1st parity cows with SCC > 150,000 cells/mL and 2+ parity cows with an SCC > 250,000 cells/mL treated with an intramammary antibiotic at dry off
[6]ST2 = 1st parity cows with SCC > 100,000 cells/mL and 2+ parity cows with an SCC > 150,000 cells/mL treated with an intramammary antibiotic at dry off
[7]ST3 = 1st parity cows with SCC > 50,000 cells/mL and 2+ parity cows with an SCC > 100,000 cells/mL treated with an intramammary antibiotic at dry off

Figure 3.13. Changes in the difference between the cost of blanket dry cow therapy[1] and selective dry cow therapy[2] (ST3) scheme as clinical mastitis incidence rate of the ST scheme increases in simulated dairy herds with low[3], average[4], and high[5] somatic cell counts.



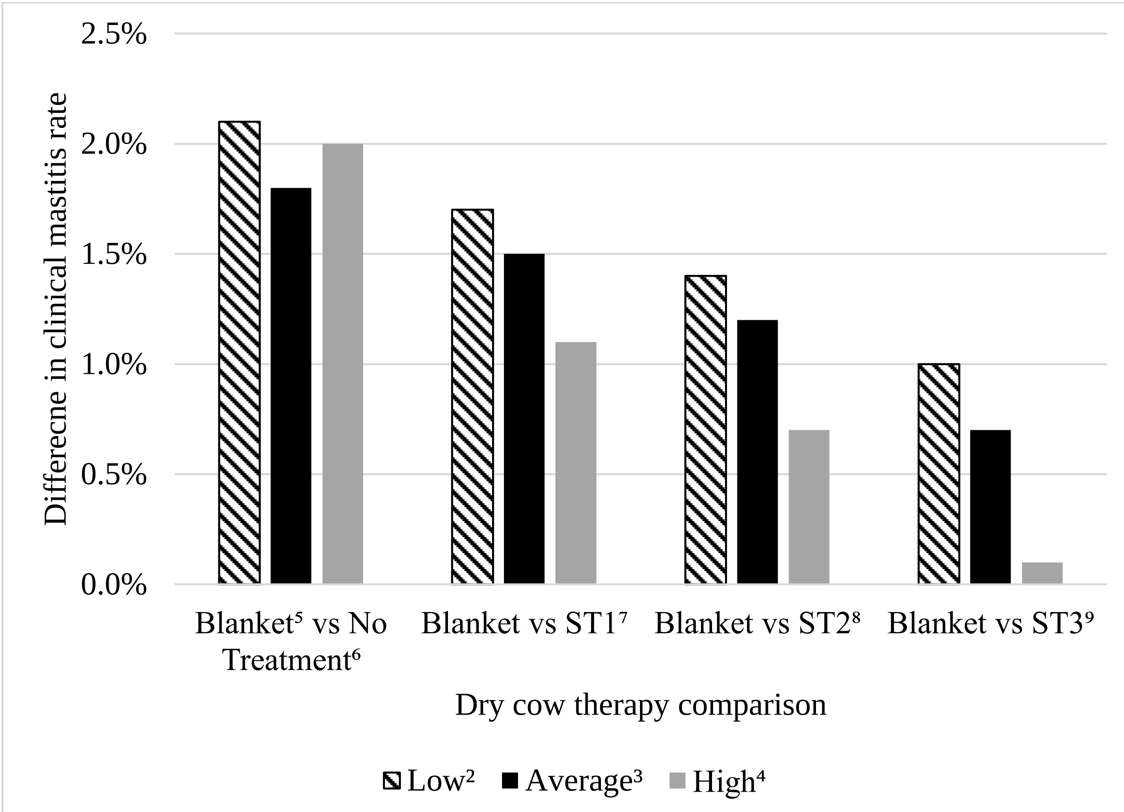
[1]Blanket dry cow therapy = all cows treated with intramammary antibiotic
[2]Selective dry cow therapy scheme = 1st parity cows with SCC > 50,000 cells/mL and 2+ parity cows with an SCC > 100,000 cells/mL treated with an intramammary antibiotic at dry off. Defined as ST3 in text of paper.
[3]Low SCC herd had a SCC of 109,000 cells/ml
[4]Average SCC herd had a SCC of 251,000 cells/mL
[5]High SCC herd had a SCC of 393,000 cells/mL

Figure 3.14. Frequency of a 1,000 iteration simulation in which blanket dry cow therapy cost less than different dry cow therapy schemes in simulated dairy herds when comparing mastitis incidence rates.



[1]Low SCC herd had a SCC of 109,000 cells/ml
[2]Average SCC herd had a SCC of 251,000 cells/mL
[3]High SCC herd had a SCC of 393,000 cells/mL
[4]Blanket therapy = all cows received intramammary antibiotics at dry off
[5]No treatment = no cows received intramammary antibiotics at dry off
[6]ST1 = 1st parity cows with SCC > 150,000 cells/mL and 2+ parity cows with an SCC > 250,000 cells/mL treated with an intramammary antibiotic at dry off
[7]ST2 = 1st parity cows with SCC > 100,000 cells/mL and 2+ parity cows with an SCC > 150,000 cells/mL treated with an intramammary antibiotic at dry off
[8]ST3 = 1st parity cows with SCC > 50,000 cells/mL and 2+ parity cows with an SCC > 100,000 cells/mL treated with an intramammary antibiotic at dry off

Figure 3.15. The maximum difference[1] in the weighted average clinical mastitis incidence rate in which a compared dry cow therapy scheme cost less than blanket dry cow therapy in simulated dairy herds.



[1]Difference = mastitis incidence rate using respective dry cow therapy scheme minus mastitis incidence rate using BT

[2]Low SCC herd had a SCC of 109,000 cells/ml

[3]Average SCC herd had a SCC of 251,000 cells/mL

[4]High SCC herd had a SCC of 393,000 cells/mL

[5]Blanket therapy = all cows received intramammary antibiotics at dry off

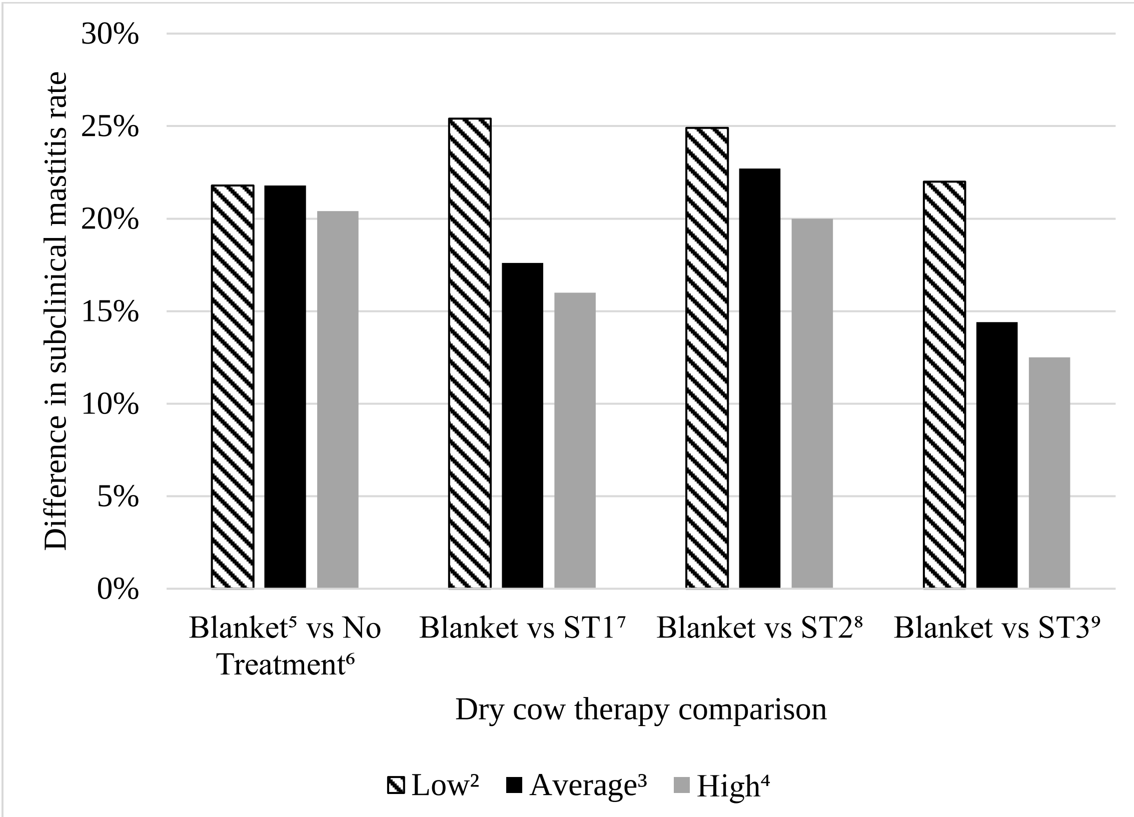
[6]No treatment = no cows received intramammary antibiotics at dry off

[7]ST1 = 1st parity cows with SCC > 150,000 cells/mL and 2+ parity cows with an SCC > 250,000 cells/mL treated with an intramammary antibiotic at dry off

[8]ST2 = 1st parity cows with SCC > 100,000 cells/mL and 2+ parity cows with an SCC > 150,000 cells/mL treated with an intramammary antibiotic at dry off

[9]ST3 = 1st parity cows with SCC > 50,000 cells/mL and 2+ parity cows with an SCC > 100,000 cells/mL treated with an intramammary antibiotic at dry off

Figure 3.16. The maximum difference[1] in the weighted average subclinical mastitis incidence rate in which a compared dry cow therapy scheme cost less than blanket dry cow therapy in simulated dairy herds.



[1]Difference = mastitis incidence rate using respective dry cow therapy scheme minus mastitis incidence rate using BT

[2]Low SCC herd had a SCC of 109,000 cells/ml

[3]Average SCC herd had a SCC of 251,000 cells/mL

[4]High SCC herd had a SCC of 393,000 cells/mL

[5]Blanket therapy = all cows received intramammary antibiotics at dry off

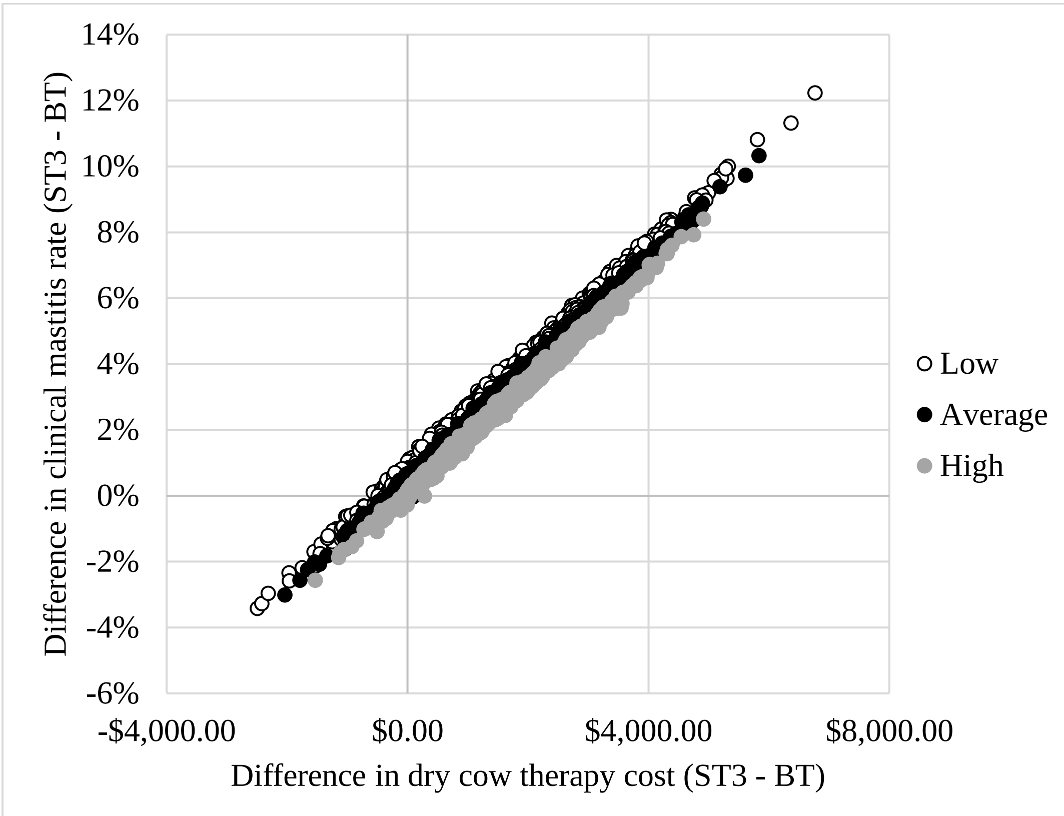
[6]No treatment = no cows received intramammary antibiotics at dry off

[7]ST1 = 1st parity cows with SCC > 150,000 cells/mL and 2+ parity cows with an SCC > 250,000 cells/mL treated with an intramammary antibiotic at dry off

[8]ST2 = 1st parity cows with SCC > 100,000 cells/mL and 2+ parity cows with an SCC > 150,000 cells/mL treated with an intramammary antibiotic at dry off

[9]ST3 = 1st parity cows with SCC > 50,000 cells/mL and 2+ parity cows with an SCC > 100,000 cells/mL treated with an intramammary antibiotic at dry off

Figure 3.17. Differences in the cost of blanket dry cow therapy[1] (BT) and selective dry cow therapy[2] (ST3) scheme by the difference[3] in clinical mastitis incidence rate of ST in dairy herds with low[4], average[5], and high somatic cell counts[6].



[1]Blanket dry cow therapy = all cows treated with intramammary antibiotic

[2]Selective dry cow therapy scheme = 1st parity cows with SCC > 50,000 cells/mL and 2+ parity cows with an SCC > 100,000 cells/mL treated with an intramammary antibiotic at dry off. Defined as ST3 in text of paper.

[3]Difference = mastitis incidence rate when using ST3 minus mastitis incidence rate using BT

[3]Low SCC herd had a SCC of 109,000 cells/ml

[4]Average SCC herd had a SCC of 251,000 cells/mL

[5]High SCC herd had a SCC of 393,000 cells/mL

4) CHAPTER FOUR

The effect of milk pricing formula on gross milk check payments to Southeastern United States dairy farmers

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INTRODUCTION

Since January 1st, 2000, after the passing of the Federal Agriculture Improvement and Reform Act of 1996, US dairy farmers have been paid for milk with two different pricing formulas. All but four of the Federal Milk Marketing Orders (FMMO) are paid using multiple component pricing **(MCP)**. Of the four FMMOs that do not use the multiple component pricing scheme, three are in the Southeastern United States (Appalachia (5), Southeast (7), and Florida (6)). In 2018, a dairy interest group in the Southeast submitted hearing requests to have the USDA potentially change the milk pricing structure in the Southeast and Appalachia FMMO. The hearing request proposed the FMMOs change to a multiple component pricing scheme (USDA Agricultural Marketing Service, 2018b). The interest in the change in pricing structure comes with the question, how would a multiple component pricing scheme impact the farm gate milk check to dairy farmers in the Southeast?

CURRENT PRICING SCHEME

The Southeastern United States is considered a milk deficit area, meaning that fluid milk production in the region does not satisfy the processors' demand. Demand is statisfied by shipping milk in from outside marketing orders. Because of the need for fluid milk in the Southeast, milk is priced to account for the total volume shipped. Milk in the Appalachia, Southeast, and Florida FMMO is valued using a skim-fat pricing scheme. In the skim-fat pricing structure, the farmer is paid for the amount of skim (fluid) milk and butterfat that the farm produces. Milk is valued with the skim-butterfat pricing scheme using the following formula:

$$Milk\ value\ (\$/_{cwt}) = \left[((lbs\ of\ total\ milk\ produced - lbs\ of\ fat)/100) * skim\ milk\ price\ (\$/_{cwt})\right] + (\left[lbs\ of\ fat\ produced * butterfat\ price\ (\$/_{lb})\right]$$

By paying farmers for the amount of skim milk they produce, total volume is encouraged to help meet the processor demand. However, dairy farmers are not paid for other components, like protein, which is vital for cheese production. One reason for the difference in pricing schemes may be the lack of cheese plants in the Southeast. According to Dairy Foods (2019), the Southeast FMMO has three cheese plants, and Appalachia has two. However, each FMMO has 30 fluid milk plants.

MULTIPLE COMPONENT PRICING

Federal milk marketing orders employing the MCP scheme value milk based on its fat, protein, and other solids yields. An additional consideration in the MCP system is the producer price differential. Producer price differential accounts for the value of all of the milk produced in an FMMO minus the cost of production of manufactured dairy products. Some FMMOs that are using the multiple component pricing scheme also pay for milk quality with a somatic cell count **(SCC)** adjustment. A SCC adjustment is implemented as a penalty for herds with an SCC above 350,000 cells/mL. Overall, multiple component pricing values milk using the following equation:

$$
\begin{aligned}
Milk\ value\ ({}^{\$}/_{cwt}) &= \left(lbs\ of\ fat\ shipped * fat\ price\ \left({}^{\$}/_{lb}\right)\right) \\
&+ \left(lbs\ of\ protein\ shipped * protein\ price\ \left({}^{\$}/_{lb}\right)\right) \\
&+ \left(lbs\ of\ other\ solids\ shipped * other\ solids\ price\ \left({}^{\$}/_{lb}\right)\right) \\
&+ \left(\left(\frac{total\ milk\ yield\ shipped}{100}\right)\right. \\
&\left. * producer\ price\ differential\ \left({}^{\$}/_{cwt}\right)\right) - SCC\ adjustment
\end{aligned}
$$

MCP VS SKIM-BUTTERFAT PRICING IN THE SOUTHEAST

Newton (2014) determined that the Southeast region, including the Southeast, Appalachia, and Florida FMMO would have increased producer milk value by a total of $68 million from 2006 to 2013 if milk were priced using MCP. However, this additional value may not come back directly to the farmer. Newton (2014) indicates that benefits to the farmer would depend on the FMMO response to MCP. Marketing orders may redistribute pool dollars or change premium structures, which could impact farm milk checks. One pool adjustment that is commonly made in FMMOs is transportation adjustments. Transportation adjustments are made for milk that is shipped from supply to distribution plants when Class I milk is needed (Congressional Research Service, 2017). Adjustments in transportation costs could impact milk prices paid to the farmer.

USING HERD INFORMATION

Utilizing Dairy Records Management System (DRMS) test day data to evaluate individual farms allows for a more accurate representation of the returns to a farm if an MCP scheme was adopted. Overall, 43,814 herd test day records from 2012 through 2018 were collected and analyzed. Using the MCP equation above, each cow’s test day fat, protein, and other solids percent were multiplied by their respective prices to determine the value of milk each cow produced during that test day. Pricing values in each of the equations were collected from the USDA Agricultural Marketing Service (2019). The multiple component pricing values were then compared to the value of milk using the skim-butterfat pricing equation.

MCP VS SKIM-BUTTERFAT PRICING AT A HERD LEVEL

When examining the prices by the milk produced by each farm per test day, multiple component pricing resulted in a higher milk value ($20.74/cwt) compared to when milk was priced with the skim-butterfat value ($20.51/cwt). Farms had the potential to make $0.23/cwt more per test day when milk was priced using the multiple component pricing scheme. When comparing across FMMO, milk value was higher when priced with multiple component pricing than when priced with skim-butterfat pricing for both the Appalachia and Southeast FMMO across all years (Figure 4.1). The Southeast FMMO had the greatest range in differences from $0.27/cwt in 2017 to $0.72/cwt in 2014. The only year in which Appalachia had greater differences than the Southeast was 2017. In 2017, producer price differentials in the Southeast and Appalachia were within $0.25/cwt of each other, but in most other years the Southeast received around $0.50 more than Appalachia.

When comparing milk values at a state level, MCP resulted in a higher value across all states (Figure 4.2). Observed differences from state to state could be due to production as well as the producer price differential payments. States that were in the Southeast FMMO tended to have higher milk values. Kentucky and Tennessee are unique because they are split between two different FMMOs. In the data presented in Figure 4.2, Kentucky farms are assumed to ship milk to the Appalachia FMMO and their prices are lower than other states. However, when Kentucky farms ship milk to the Southeast FMMO the prices they would receive are closer to the other states.

Farms that were primarily Holstein (≥ 75% Holstein cows tested on test day) were more profitable when milk was priced using the skim-butterfat pricing scheme. Milk price differed by \$0.01/cwt by breed type when priced with MCP (Figure 4.3). These results may suggest that when milk is priced using MCP, the value of protein helps herds that are not primarily Holstein close the gap on the difference in milk value from Holstein herds.

When the value of skim milk contributed the most to the total milk value, farmers were paid more than when butterfat contributed the most to the total value. When the value of skim milk was ≥ 50% of the total milk value, under the skim-butterfat pricing scheme, farmers made \$3.06 more per cwt than if the value paid for fat made up more than 50% of the total milk value. For MCP, when the value of protein contributed the most to the total value of milk, dairy farmers were paid \$2.78 more per cwt than when the value of fat contributed the most.

If milk protein percentage ranged from 2.92% to 3.02%, skim-butterfat pricing paid more per cwt of milk. Even when fat production was relatively high (3.87% to 4.12%), only 38% of test day records resulted in MCP having a higher milk value (Table 4.1). Farms that had a milk protein percentage over 3.02% were paid more when milk was priced using MCP. When protein percent increased above 3.02% greater than 88.4% of test days resulted in milk being more valuable when priced with MCP

TAKE-HOME MESSAGE

Overall, when milk was valued using MCP, farmers were paid more per test day. When milk was valued using the skim-butterfat formula, producers were paid more when the value of skim milk contributed the most to the total value of milk. So, increasing total milk yield may be more profitable than trying to improve specific components. Under the MCP scheme, farms in which the value of protein contributed the most to the total milk value were paid more per test day. Farms with below-average protein production (< 3.03%) would be paid more under a skim-butterfat pricing scheme.

Farms that were primarily Holstein (≥ 75% Holstein cows tested on test day) were paid more than other herds when milk was priced using skim-butterfat pricing. However, when milk was priced using MCP, the value of milk between the two different herd types was less than $0.01/cwt. Bailey et al. (2005) concluded that increasing the overall volume of milk rather than focusing on specific components led to more value when comparing the value of milk using MCP in Holstein and Jersey herds. The difference in results suggests that a more complete analysis should be completed with the current dataset.

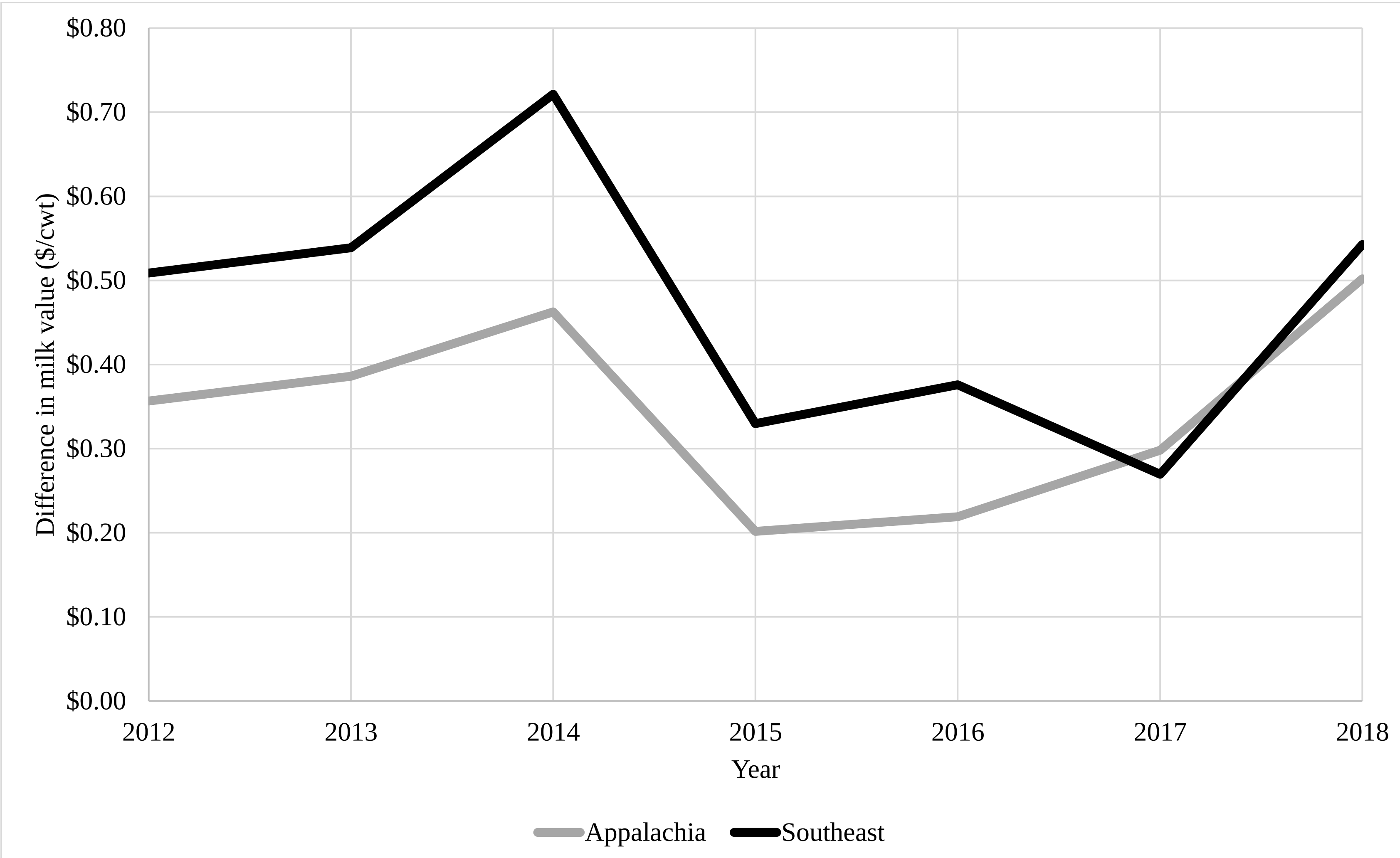
The results of the research presented are preliminary. Values presented in this paper are from mean observations only. Statistical analyses are being completed to determine if differences between the pricing schemes are statistically significant. Additional research is being done testing the interaction of pricing and herd specific variables. These results are also based on farm-level data and do not consider how a pricing scheme change may affect the overall price change to dairy farmers. For assumptions made in the current analysis refer to the Appendix.

Table 4.1. Milk value under multiple component (MCP) and skim-butterfat (S-BF) pricing schemes associated with herd average protein and fat production.

Protein	Fat	MCP Value	S-BF Value	Frequency[1]
2.92% to 3.02%	3.30% to 3.56%	$19.68	$19.78	14.9%
2.92% to 3.02%	3.57% to 3.87%	$20.17	$20.21	26.2%
2.92% to 3.02%	3.87% to 4.12%	$20.82	$20.84	38.1%
3.03% to 3.16%	3.30% to 3.56%	$20.23	$20.05	88.4%
3.03% to 3.16%	3.57% to 3.87%	$20.77	$20.52	93.6%
3.03% to 3.16%	3.87% to 4.12%	$21.35	$21.05	94.8%
3.17% to 3.29%	3.30% to 3.56%	$20.63	$20.13	96.1%
3.17% to 3.29%	3.57% to 3.87%	$21.24	$20.71	95.2%
3.17% to 3.29%	3.87% to 4.12%	$21.92	$21.35	95.6%

[1]Frequency = the percent of test day observations in which MCP led to higher milk value.

Figure 4.1. The difference[1] in the mean value of milk when milk is priced using multiple component pricing and skim-butterfat pricing schemes by year for Appalachia and Southeast Federal Milk Marketing Orders.



[1]Difference = multiple component pricing minus skim-butterfat

Figure 4.2. Mean milk value ($/cwt) when milk is valued using multiple component pricing (MCP) and skim-butterfat (S-BF) pricing schemes by state.

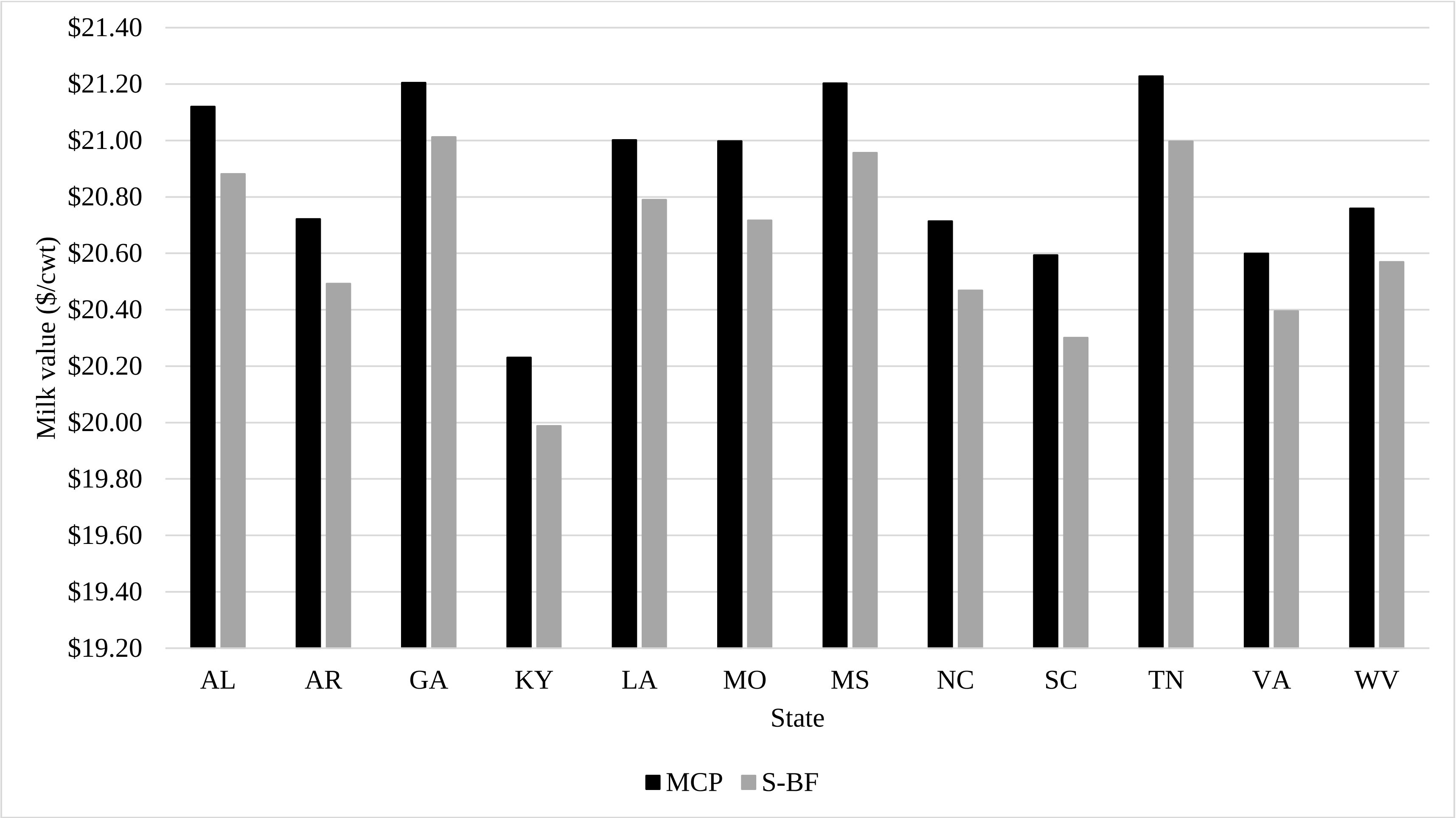
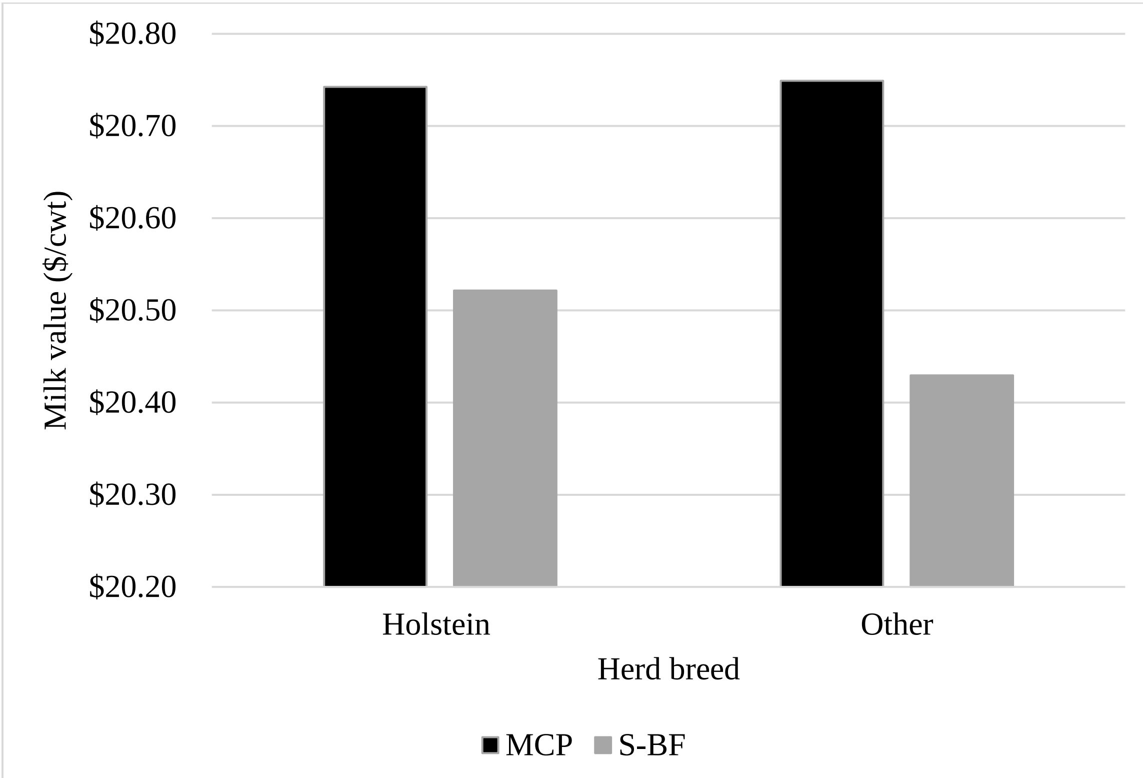


Figure 4.3. Mean value of milk ($/cwt) under multiple component price (MCP) and skim-butterfat (S-BF) pricing schemes by herd breed.



[1]Holstein herds were defined as a herd with ≥ 75% Holstein cows on test day
[2]Other herds were defined as a herd with less than 75% Holstein cows on test day

RESEARCH SUMMARY

This dissertation had three objectives, all based on current trends in the US dairy industry. The legal limit of somatic cell count (SCC) is 750,000 cells/mL in the US. However, within the last 10 years dairy processors are demanding lower SCC thresholds. To meet these demands, milk quality management on farms is very important. However, when profit margins are tight, dairy farmers may be reluctant to adopt new management practices. Throughout our literature search, we found little research being done examining the economics of SCC management. So, the first objective was to determine the cost of a particular herd SCC and how costs change after management practices have been implemented to control SCC. This was accomplished by using stochastic simulation to model how the adoption of different cost management practices affects the total change in cost of herd SCC. The benefits of management practice adoption included increased herd milk yield and potential milk quality premiums from decreasing the herd SCC. Results from our analysis indicate that by adopting management practices, the simulated farms could significantly lower their cost of SCC. These results were highly dependent on the farms' base SCC and how close they were to a SCC premium. When premiums for milk quality were offered, economics associated with the adoption of management practices became more beneficial.

However, when premiums were not offered, the economics benefits associated with management practice adoption dramatically decreased to the point the high cost management practice was no longer feasible to the herd with a low SCC. The lack of benefit indicates that, in some situations, if farms have a low SCC they may actually loose profit by adopting practices to decrease their SCC even further.

In our analysis, farms could benefit by almost $12,000 per year by receiving a premium of $0.005 for every kg of milk produced. Research has shown that providing farmers an incentive, they are more willing to meet the demands brought upon them. Though economic losses associated with milk loss due to a high SCC are indirect, they too should be thought of as an incentive by farmers. In our simulations, economic losses from lost milk production alone were as high as $15,000/farm per yr. By educating dairy farmers on the indirect costs of SCC farmers we hope to show the additional incentive to lowering herd SCC.

One area that was not modeled in our research was the impact of management practice and other diseases of dairy cattle. For example, the adoption of certain management practices might have a positive effect on transition cow diseases or lameness. By not accounting for additional diseases the benefits of the management practices model may be underestimated. Future research that modeled the effects of management practice adoption on multiple diseases would provide a more accurate economic benefit to the farmer.

Because of pressure to decrease the use of antibiotics in animal agriculture, one management practice that might soon be taken away from dairy farmers in the US is the use of blanket dry cow therapy. When reviewing the literature, many studies comparing the economics of blanket vs. selective dry cow therapy were based on a Dutch dairy system. Authors could find little to no research comparing the costs in US dairy herds. So, the second objective was to determine if selective dry cow therapy is more economical compared to blanket dry cow therapy by varying selective dry cow therapy selection criteria. Research was completed by modeling the cost of dry cow therapy to simulated dairy farms using stochastic simulation. In most simulation iterations, the cost of blanket dry cow therapy to the farms was less than selective dry cow therapy. The average costs of blanket and selective dry cow therapy were significantly less than when the simulated farms used no therapy at all. When modeling the costs of dry cow therapy, we considered the cost of labor, the costs of clinical and subclinical mastitis, and mastitis incidence rate.

Unlike other published data, we assumed that blanket dry cow therapy and selective dry cow therapy would have different labor costs. We assumed that selective dry cow therapy would be carried out by management labor at a higher hourly wage. The assumption was also made that the time of treatment would be longer to account for viewing of records to determine whether cows needed to receive treatment and sorting of cows that needed to be dried off. By completing the labor analysis, we concluded that labor costs of blanket dry cow therapy would have to increase to unrealistic levels before other therapy options would become economically feasible. Therefore, labor savings should not be the only consideration if when choosing dry cow therapy options.

Overall, results were dependent on the cost of clinical mastitis and clinical and subclinical mastitis incidence rates. As both the cost of clinical mastitis and mastitis incidence rates decreased, selective dry cow therapy became more economical. However, a large portion of the cost of a case of mastitis is due to milk loss. We did not consider milk price when calculating the cost of dry cow therapy treatments. Future research examining the effect of milk price on optimal treatment options would provide farmers with more information in making dry cow therapy treatment decisions.

Because farmers in the US may be required to use selective dry cow therapies in the future. Our research was focused at costs at the farm level. However, the limitation of the use of blanket dry cow therapy will most likely have impacts on the entire dairy industry. More research is needed on how a policy change might affect milk supply and therefore the economics at not only the farm level but the processor and consumer levels as well.

Within the last year, different dairy industry groups in the Southeastern US have sent hearing requests to the United States Department of Agriculture to change how milk is priced in the Appalachia and Southeast Federal Milk Marketing Orders. Currently, milk pricing schemes in the two Milk Marketing Orders price milk based on the skim and butterfat value. Most other Federal Milk Marketing Orders price milk using multiple component pricing, which considers the values of fat, protein and other solids in the milk. Most research comparing the two pricing schemes has looked at the overall impact in the Southeast; very little research has been done at the farm level. The third objective of our research was to provide insight into the potential differences in farm gate milk checks when milk is priced under different pricing schemes. To accomplish the third objective, the milk pricing schemes were compared using individual cow production data from farms in the Appalachia and Southeast Federal Milk Marketing Orders. In a preliminary analysis of the data, pricing milk with multiple component pricing led to higher milk values. However, results were dependent on milk component production of the farms analyzed. Farms that had lower protein production (< 3.0%) were paid less when milk was priced using the multiple component pricing methods compared to the skim-butterfat formula. Preliminary results also indicated that pricing variables specific to the multiple component pricing formula may affect whether or not dairy farmers in the Southeast would benefit from a pricing scheme change. More research is needed to determine how herd demographics and price data may affect prices at a farm level.

Because milk in the Southeast is primarily used for fluid dairy products future research should focus on how the demand for fluid products is decreasing while the demand for processed dairy products is increasing. This switch in demand may favor a pricing change at the farm level but the total economic impact of the dairy industry at the processor level should also be considered.

APPENDIX

Table A.1. Milk yield losses (kg/cow/yr) associated with a herd somatic cell count (SCC) threshold Hand et al. (2012).

SCC Threshold (SCC*1,000 cells/mL)		Lactation		
Upper SCC	Lower SCC	1	2	3+
100	200	165	348	381
200	300	196	372	423
300	400	253	444	503
400	500	314	526	561
500	600	327	555	614

In Chapter 3 of this dissertation, estimates for mastitis incidence rates were calculated using the steps shown in the following tables. The bolded/italicized values will be used in an example equation under each table.

Table A.2. Step 1: Mastitis incidence rates used by Scherpenzeel et al. (2018) in a dry cow therapy cost analysis and used in the US dairy systems model as a base for mastitis incidence rate adjustment.

			Incidence rate in next lactation			
			Clinical Mastitis		Subclinical Mastitis	
SCC Group	Dry off SCC (cells/mL*1,000)	Parity	Treat (+)	Treat (-)	Treat (+)	Treat (-)
1	0 to 50	1	9.90%	11.80%	4.80%	7.20%
2	51 to 100	1	9.10%	10.80%	10.60%	19.00%
3	101 to 150	1	13.50%	18.20%	8.20%	17.70%
4	> 150	1	14.40%	20.00%	11.30%	25.00%
5	0 to 50	2+	12.80%	20.10%	7.30%	17.30%
6	51 to 100	2+	15.20%	26.80%	13.60%	18.80%
7	101 to 150	2+	9.00%	19.10%	15.70%	24.80%
8	151 to 250	2+	16.50%	24.10%	18.40%	31.70%
9	> 250	2+	16.60%	24.40%	22.60%	37.40%

Table A.3. Step 2: Each value in Table A.1 is divided by the value in column Subclinical mastitis Treat(+) by row[1].

			Incidence rate in next lactation			
			Clinical Mastitis		Subclinical Mastitis	
SCC Group	Dry off SCC (cells/mL*1,000)	Parity	Treat (+)	Treat (-)	Treat (+)	Treat (-)
1	0 to 50	1	2.1	2.5	1.0	1.5
2	51 to 100	1	0.9	1.0	1.0	1.8
3	101 to 150	1	1.6	2.2	1.0	2.2
4	> 150	1	1.3	1.8	1.0	2.2
5	0 to 50	2+	1.8	2.8	1.0	2.4
6	51 to 100	2+	1.1	2.0	1.0	1.4
7	101 to 150	2+	0.6	1.2	1.0	1.6
8	151 to 250	2+	0.9	1.3	1.0	1.7
9	> 250	2+	0.7	1.1	1.0	1.7

[1]Example equation: 0.099/0.048 = **2.1**

Table A.4. Step 3: Mastitis incidence rates that were derived from Dairy Records Management Systems test day data.

			Incidence rate in next lactation			
			Clinical Mastitis		Subclinical Mastitis	
Group	Dry off SCC (cells/mL*1,000)	Parity	Treat (+)	Treat (-)	Treat (+)	Treat (-)
1	0 to 50	1			9.05%	
2	51 to 100	1			11.75%	
3	101 to 150	1			13.72%	
4	> 150	1			19.87%	
5	0 to 50	2+			13.72%	
6	51 to 100	2+			16.03%	
7	101 to 150	2+			18.36%	
8	151 to 250	2+			21.18%	
9	> 250	2+			29.19%	

Table A.5. Step 4: Each value in Table A.2 is multiplied by the column Subclinical Mastitis Treat(+) in Table A.3 by row[1].

			Incidence rate in next lactation			
			Clinical Mastitis		Subclinical Mastitis	
Group	Dry off SCC (cells/mL*1,000)	Parity	Treat (+)	Treat (-)	Treat (+)	Treat (-)
1	0 to 50	1	18.7%	22.2%**	9.1%	13.6%
2	51 to 100	1	10.1%	12.0%	11.8%	21.1%
3	101 to 150	1	22.6%	30.5%	13.7%	29.6%
4	> 150	1	25.3%	35.2%	19.9%	44.0%
5	0 to 50	2+	24.1%	37.8%**	13.7%	32.5%
6	51 to 100	2+	17.9%	31.6%	16.0%	22.2%
7	101 to 150	2+	10.5%	22.3%	18.4%	29.0%
8	151 to 250	2+	19.0%	27.7%	21.2%	36.5%
9	> 250	2+	21.4%	31.5%	29.2%	48.3%

[1]Example equation: 2.1*0.0905 = **18.7%**

[2]Because lowest SCC groups had the highest incidence rate as indicated by (**) only the values for Groups 4 and 9 were kept.

Table A.6. Step 5: The percent change was calculated by row from groups 4 to 1 and 9 to 5 for column Subclinical Mastitis Treat(+)[1].

			Incidence rate in next lactation				
			Clinical Mastitis		Subclinical Mastitis		
Group	Dry off SCC (cells/mL*1,000)	Parity	Treat (+)	Treat (-)	Treat (+)	Treat (-)	% Change
1	0 to 50	1			9.1%		-0.23
2	51 to 100	1			11.8%		-0.14
3	101 to 150	1			13.7%		-0.31
4	> 150	1			19.9%		
5	0 to 50	2+			13.7%		-0.14
6	51 to 100	2+			16.0%		-0.13
7	101 to 150	2+			18.4%		-0.13
8	151 to 250	2+			21.2%		-0.27
9	> 250	2+			29.2%		

[1]Example equation: (0.137-0.199)/0.199 = -0.31
Example equation: (0.212 – 0.292)/0.292 = -0.27

Table A.7. Step 6: The percent change column is applied to Groups 4 and 9 (values from Table A.4) and carried on throughout each row[1].

			Incidence rate in next lactation				
			Clinical Mastitis		Subclinical Mastitis		
Group	Dry off SCC (cells/mL*1,000)	Parity	Treat (+)	Treat (-)	Treat (+)	Treat (-)	% Change
1	0 to 50	1			9.05%		-0.23
2	51 to 100	1	14.97%		11.75%		-0.14
3	101 to 150	1	17.48%		13.72%		-0.31
4	> 150	1	25.32%	35.17%	19.87%	43.96%	
5	0 to 50	2+			13.72%		-0.14
6	51 to 100	2+			16.03%		-0.13
7	101 to 150	2+	13.49%		18.36%		-0.13
8	151 to 250	2+	15.56%		21.18%		-0.27
9	> 250	2+	21.44%	31.51%	29.19%	48.31%	

[1]Example equation: 0.2532 + (0.2532 * -0.31) = 17.48%
0.1748 + (0.1748 * -0.14) = 14.97%
Example equation: 0.2144 + (0.2144 * -0.27) = 15.56%
0.1556 + (0.1556 * -0.13) = 13.49%

Table A.8. The final estimates for mastitis incidence rate used in Chapter 3 of this dissertation to calculate the costs of dry cow therapy.

			Incidence rate in next lactation			
			Clinical Mastitis		Subclinical Mastitis	
Group	Dry off SCC (cells/mL*1,000)	Parity	Treat (+)	Treat (-)	Treat (+)	Treat (-)
1	0 to 50	1	11.53%	16.02%	9.05%	20.02%
2	51 to 100	1	14.97%	20.80%	11.75%	26.00%
3	101 to 150	1	17.48%	24.28%	13.72%	30.35%
4	> 150	1	25.32%	35.17%	19.87%	43.96%
5	0 to 50	2+	10.08%	14.81%	13.72%	22.70%
6	51 to 100	2+	11.77%	17.31%	16.03%	26.53%
7	101 to 150	2+	13.49%	19.82%	18.36%	30.38%
8	151 to 250	2+	15.56%	22.87%	21.18%	35.05%
9	> 250	2+	21.44%	31.51%	29.19%	48.31%

State and Herd Data used in Chapter 4:

States included in the analysis were assigned to the following Federal Milk Marketing Orders:

Appalachia:
North Carolina
South Carolina
Kentucky
Virginia

Southeast:
Louisiana
Arkansas
Missouri
Tennessee
Alabama
Mississippi
Georgia

Individual cow test day data were cleaned using the following steps:

1. Lactations had to be between 1 and 10.
2. Test day – days in milk were between 1 and 610
3. Milk yield was greater than the 1st percentile – 4.53 kg/day
4. Test day protein had to fall between the 1st and 99th percentiles – 1% to 5%
5. Test day fat had to fall between the 1st and 99th percentiles – 1% to 7%

After cleaning cow level data herds had to meet the following criteria

1. Had to have at least 20 cows at each test day meet the criteria above
2. Average protein production had to fall within the 10th and 90th percentiles – 2.92% to 3.28%
3. Average fat production had to fall within the 10th and 90th percentiles – 3.31% to 4.12%
4. Average milk yield had to fall within the 1st and 99th percentiles 6.35 kg to 55.79 kg
5. One herd was removed for size being greater than 20,000 cows
6. After cleaning of herd data total herd test day records totaled 43,814

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VITA

Derek Thomas Nolan grew up on a dairy farm in Northeast Iowa. Upon graduation of Startmont High School in 2009, he attended Iowa State University. While at Iowa State, Derek served as President of the Iowa State Dairy Science Club and was a member of the Dairy Challenge Team. He was also a member of the College of Agriculture and Life Sciences Student Council. Derek graduated from Iowa State University with a Bachelor's Degree in Dairy Science in 2013.

Derek completed his MS at the University of Kentucky in 2017. While studying under Dr. Jeffrey Bewley, his work focused on milk quality management and economics. Derek has presented his work at annual American Dairy Science Association and National Mastitis Council meetings. He has also presented at two international meetings in Brazil and Denmark.

Upon completion of his MS, Derek began his PhD at the University of Kentucky with Drs. Roberta Dwyer and Tyler Mark. His PhD work was focused on milk quality economics and milk pricing.

While at the University of Kentucky, Derek has served as the University of Kentucky Dairy Judging coach and as an assistant coach of the University of Kentucky Dairy Challenge Team. At the university level, Derek is a member of Gamma Sigma Delta and was awarded Master's Student of the Year in 2015. At a national level, Derek served as treasurer of the American Dairy Science Association-Graduate Student Division and is also a member of the National Mastitis Council.