EPIDEMIOLOGY OF BOVINE RESPIRATORY DISEASE AND MORTALITY IN

COMMERCIAL FEEDLOTS

by

ABRAM HEATH BABCOCK

B.A., Colorado State University, 2004
M.S., Kansas State University, 2006

AN ABSTRACT OF A DISSERTATION

submitted in partial fulfillment of the requirements for the degree

DOCTOR OF PHILOSOPHY

Department of Diagnostic Medicine/Pathobiology
College of Veterinary Medicine

KANSAS STATE UNIVERSITY
Manhattan, Kansas

2010

Abstract

The objective of my research was to quantify epidemiologic parameters associated with feedlot mortality and bovine respiratory disease complex (BRDC); the most significant cause of morbidity in U.S. feeder cattle. We conducted four retrospective studies utilizing individual health and cumulative cohort-level feedlot data. We developed a database that represented 33 U.S. feedlots from six states over ten years. Each project used a subset of these data.

We found that the timing of BRDC was associated with important performance and health indices. In the first study, we evaluated the effect of the timing of individual BRDC treatments on standardized net returns. We found important performance and health measures (e.g. hot carcass weight and number treatments) driving net return differences associated with the timing of BRDC. For the second cohort-level study, we classified temporal patterns of BRDC, and evaluated associations among temporal patterns and performance and health. Temporal patterns were significantly associated with mean daily weight gain, days on feed, carcass weight, yield grade, quality grade, cumulative mortality, and retreatment risk.

We also evaluated combined mortality and culling risks and quantified the effects of risk factors using count models. All risk factors (arrival weight, gender, and arrival month) were significant and the effects were modified by one another; effects of these covariate patterns have been impossible to quantify in smaller studies.

Finally, we assessed the ability of regression models to predict cumulative BRDC morbidity based on arrival risk factors; then assessed the additional value of incorporating daily BRDC morbidity and mortality information. The percent of correctly classified cohorts did increase across days, but the effect of day was modified by weight, month, and feedlot. Information on daily morbidity was beneficial in predicting cumulative morbidity, but daily mortality provided little benefit.

Our database containing animal health and cohort-level data allowed us to generate novel information on the effects of the timing of BRDC in feedlot populations. We also demonstrated effects of covariate patterns on adverse health outcomes that heretofore had been difficult to quantify. Finally, we showed that a predictive model for BRDC may be useful for the feedlot industry; this model should be further developed with future research.

EPIDEMIOLOGY OF BOVINE RESPIRATORY DISEASE AND MORTALITY IN
COMMERCIAL FEEDLOTS

by

ABRAM HEATH BABCOCK

B.A., Colorado State University, 2004
M.S., Kansas State University, 2006

A DISSERTATION

submitted in partial fulfillment of the requirements for the degree

DOCTOR OF PHILOSOPHY

Department of Diagnostic Medicine/Pathobiology
College of Veterinary Medicine

KANSAS STATE UNIVERSITY
Manhattan, Kansas

2010

Approved by;

Co-Major Advisor
Dr. D.G. Renter

Approved by;

Co-Major Advisor
Dr. B.J. White

Copyright

Abram Heath Babcock

2010

Abstract

The objective of my research was to quantify epidemiologic parameters associated with feedlot mortality and bovine respiratory disease complex (BRDC); the most significant cause of morbidity in U.S. feeder cattle. We conducted four retrospective studies utilizing individual health and cumulative cohort-level feedlot data. We developed a database that represented 33 U.S. feedlots from six states over ten years. Each project used a subset of these data.

We found that the timing of BRDC was associated with important performance and health indices. In the first study, we evaluated the effect of the timing of individual BRDC treatments on standardized net returns. We found important performance and health measures (e.g. hot carcass weight and number treatments) driving net return differences associated with the timing of BRDC. For the second cohort-level study, we classified temporal patterns of BRDC, and evaluated associations among temporal patterns and performance and health. Temporal patterns were significantly associated with mean daily weight gain, days on feed, carcass weight, yield grade, quality grade, cumulative mortality, and retreatment risk.

We also evaluated combined mortality and culling risks and quantified the effects of risk factors using count models. All risk factors (arrival weight, gender, and arrival month) were significant and the effects were modified by one another; effects of these covariate patterns have been impossible to quantify in smaller studies.

Finally, we assessed the ability of regression models to predict cumulative BRDC morbidity based on arrival risk factors; then assessed the additional value of incorporating daily BRDC morbidity and mortality information. The percent of correctly classified cohorts did increase across days, but the effect of day was modified by weight, month, and feedlot. Information on daily morbidity was beneficial in predicting cumulative morbidity, but daily mortality provided little benefit.

Our database containing animal health and cohort-level data allowed us to generate novel information on the effects of the timing of BRDC in feedlot populations. We also demonstrated effects of covariate patterns on adverse health outcomes that heretofore had been difficult to quantify. Finally, we showed that a predictive model for BRDC may be useful for the feedlot industry; this model should be further developed with future research.

Table of Contents

List of Figures

List of Tables

Acknowledgements

Dedication

I would like to dedicate my dissertation to my wife Elizabeth for her love, support, and willingness to put her career on hold and move to Manhattan to be with me.

Preface

Bovine respiratory disease complex (BRDC) is the most common cause of post-weaning disease in feeder cattle. Even with the advances in biologicals, pharmaceuticals and management systems, BRDC still costs the beef industry hundreds of millions of dollars each year. The epidemiology of BRDC in feedlots is the result of complex interactions of multiple pathogens, host, environment and management factors, which results in substantial variability in disease expression. Effects of risk factors involving host, environment, and management factors are often assessed in small scale studies using few feedlots and/or data aggregated at the feedlot level. Temporal effects of BRDC have been identified as important to the feedlot industry, but effects of the timing of BRDC cases are mostly based on subjective evaluation and have yet to be quantified in the literature. Feedlots routinely collect individual health and cumulative cohort-level data. Even with large quantities of data, there are information gaps on how to use these data to accurately classify population outcomes based on specific covariate patterns of cohorts at arrival to the feedlot, or to make real-time, evidenced-based decisions with regard to individual cohorts. Using these large quantities of data to quantify BRDC related outcomes and eliminating incorrect epidemiologic assumptions will have enormous benefits to the feedlot industry. The objective of this research was to utilize operational data routinely collected at commercial feedlots to evaluate how the timing of BRDC cases affects common measures of feedlot performance and health, and to quantify cohort-level patterns of BRDC based on the temporal distribution of individual animal events within a cohort. We also wanted to quantify the effects of common risk factors and their interactions on adverse health outcomes (i.e., mortality and culling). Finally, we wanted to assess the ability of regression models at predicting cumulative BRDC morbidity over the entire feeding period based on arrival risk factors, and to assess the value of adding daily BRDC morbidity and mortality information to the model. The dissertation contains the following studies:

Feedlot health and performance effects associated with the timing of respiratory disease treatment

Temporal distributions of respiratory disease events within cohorts of feedlot cattle and associations with health and performance indices

Quantifying the effects of common risk factors for combined mortality and culling risk in feedlot cattle populations using a mixed effects count model

Predicting cumulative risk of bovine respiratory disease complex using feedlot arrival data and daily morbidity and mortality counts

CHAPTER 1 - Literature Review: The epidemiology and economics of bovine respiratory disease complex

A.H. Babcock[a,b], D.G. Renter[a], B.J. White[b]

[a]Department of Diagnostic Medicine and Pathobiology, College of Veterinary Medicine, Kansas State University, Manhattan, Kansas, United States

[b]Department of Clinical Sciences, College of Veterinary Medicine, Kansas State University, Manhattan, Kansas, United States

Introduction

Even with advances and development of new vaccines and therapeutics, bovine respiratory disease complex (BRDC) is still the primary disease problem in feedlots today (Griffin et al., 1995). The 1999 United States Department of Agriculture's National Animal Health Monitoring System (NAHMS) survey showed that BRDC was four times more prevalent than acute interstitial pneumonia, the second leading cause of disease in feedlots (USDA, 2000). The cohort-level cumulative incidence of BRDC in feedlots is highly variable and ranges from 0 to 70%, but typically falls between 15 to 45% and accounts for approximately 75% of all feedlot morbidity (Kelly and Janzen, 1986; Edwards, 1996). The syndrome is responsible for approximately 45-55% of all feedlot deaths (Vogel and Parrott, 1994; Edwards, 1996). The syndrome has been estimated to account for approximately 8% of total production costs, not accounting for economic losses related to decreased performance (Griffin et al., 1995). Production costs associated with BRDC have been estimated to cost the beef industry $500 million/year (Speer et al., 2001).

The majority of BRDC research has focused on the etiology and pathogenesis, and relatively little on the epidemiology of the syndrome. The epidemiology of BRDC in feedlot systems is complex; multifactorial interactions of etiologic agent, host, and management factors result in extremely variable disease expression (Lillie, 1974; Martin et al., 1982; Ribble et al.,

1995a; Cusack et al., 2003). The objective of this literature review was to evaluate the effects of BRDC related health outcomes on feedlot performance measures, examine risk factors associated with BRDC, assess the economic impact of BRDC, and evaluate the effect of the timing of BRDC events.

Bovine respiratory disease complex and the epidemiologic triad

Bovine respiratory disease complex is a multifactorial disease syndrome that results from pathogen, host, and environmental/management factors. The interactions among factors result in an extremely variable disease expression.

Host response

Animal immunity can be broken down into two general categories innate (natural) or acquired (specific) immunity (Galyean et al., 1999). It has been documented that calves with higher plasma protein concentrations at postpartum hour 24 (proxy for successful passive colostral transfer) experience a lower incidence of BRDC pre-weaning and in the feedlot compared to animals that don't have adequate plasma protein concentrations (Wittum and Perino, 1995). Vaccination of animals prior to, or at arrival to, the feedlot can also influence the acquired immunity of feedlot animals. The literature on the efficacy of vaccines against BRDC pathogens has been mixed (Mosier, 1989; Perino and Hunsaker, 1997). Innate and acquired immunity at the time of pathogen exposure impacts the occurrence of BRDC.

Common pathogens associated with BRDC

Animals entering, or shortly after arrival to, the feedlot are likely to be exposed to most pathogens associated with BRDC within a short time after arrival (Martin and Bohac, 1986; Martin et al., 1989; Griffin, 1998; Booker et al., 1999). The major bacterial pathogens found to contribute to BRDC are *Mannheimia haemolytica*, *Histophilus somni*, *Pasteurella multocida*, and some indication that *Mycoplasma bovis* may be a primary pathogen (Apley, 2006). The most commonly isolated bacterium from feedlot animals is *Mannheimia haemolytica* (Rice et al., 2007). *Mannheimia haemolytica* is a commensal organism that is found in the nasopharynx and tonsils (Babiuk and Acres, 1984; Frank and Briggs, 1992; Frank et al., 1995). The organism has a symbiotic relationship with the animal in normal circumstances (Rice et al., 2007).

The major viral pathogens that have been associated with BRDC are infectious bovine

rhinotracheitis (IBR), bovine viral diarrhea (BVD), and bovine respiratory syncytial virus (BRSV). Parainfluenza-3, bovine coronavirus, adenovirus, rhinovirus, reovirus, and enterovirus also have been found to be associated with BRDC to a lesser extent (Kapil and Basaraba, 1997; Callan and Garry, 2002). The viruses associated with BRDC predispose the lungs to bacterial infections by limiting the respiratory tracts defense mechanisms (Callan and Garry, 2002). Specific pathogens present (bacterial, viral, or combination) may impact the clinical and epidemiologic presentation of BRDC.

Environment and management

The concept of environment with regard to the epidemiologic triad is more than climate or weather. Environmental or predisposing factors include physical, biological, and sociological milieu of animals (Martin et al., 1987). These environmental factors are referred to as "stressers" in the beef industry (Dabo et al., 2007). Stressors are defined as the psychological or physical conditions unpleasant to the animal (Jacobson and Cook, 1998). Stress caused by multiple factors of the production process of feedlot cattle is thought to have a direct impact on the immune status of an animal; however, the magnitude of stress and its effect on the immune system are difficult to quantify because stress in animals can only be vaguely defined (Grandin, 1997). The season of animal entry to the feedlot has been documented as having an impact on the incidence of BRDC (Ribble et al., 1995a). The effect of weather has been speculated, but research involving weather variables is limited (Ribble et al., 1998; Cusack et al., 2007). Management factors such as transportation, commingling, auction markets, and weaning have been found to be associated with an increase in BRDC risk (Wilson et al., 1985; Gummow and Mapham, 2000; Sanderson et al., 2008). Other management factors like the use of metaphylaxis have demonstrated positive results in decreasing BRDC incidence (Van Donkersgoed, 1992; Frank et al., 2002; Macartney et al., 2003; Cusack, 2004; Johnson et al., 2008). Many physical, biological, and sociological risk factors have been found to influence the cumulative BRDC disease burden within cohorts of feedlot cattle.

Effect of BRDC on feedlot performance

The adverse effect of BRDC on feedlot performance has been widely documented, although not all studies show a negative impact. The discrepancy may be due to the differing case definitions of BRDC throughout the literature. Case definitions may differ between

employees, days of the week, and feedlots (Corbin and Griffin, 2006). Specific case definitions are important when evaluating results from a study where the outcome is BRDC morbidity.

Average daily gain

One general assessment of feedlot animal performance is average daily gain (ADG), which is the total weight gained divided by the number of days the animal was on feed (Smith et al. 2001). When looking at healthy animals compared to animals that were treated at least once for BRDC, several authors have reported a significant reduction in average daily gain (Bateman et al., 1990; Morck et al., 1993; Wittum and Perino, 1995; Gardner et al., 1999; Snowder et al., 2006; Thompson et al., 2006; Cusack et al., 2007; Seeger et al., 2008; Montgomery et al., 2009; Reinhardt et al., 2009; Schneider et al., 2009a). These differences have ranged from as little as 0.02 kg/head/day to as large as 0.70 kg/head/day (Thompson et al., 2006; Cusack et al., 2007). Others have found no significant differences in ADG when comparing treated and untreated calves (Cole et al., 1979; Jim et al., 1993; Wittum et al., 1996; Snowder et al., 2007; Brooks et al., 2009). One study found that treated animals actually displayed significantly greater ADG compared to animals that were not treated (Roeber et al., 2001). Differing results in the literature may be due to different case definitions of BRDC between studies, or differing cattle demographics.

Mixed results also have been found for assessments of ADG and the number of BRDC treatment events for an animal. A 2006 study found no significant differences in ADG between animals that were treated once vs. multiple times (Thompson et al. 2006). Several studies have found animals that are treated more than once for BRDC display decreased ADG compared to those animals only treated once (Morck et al., 1993; Gardner et al., 1999; Roeber et al., 2001; Reinhardt et al., 2009). These results indicate that multiple treatments for BRDC may have a negative impact on ADG in feedlot cattle.

Body weight at harvest

Final body weight can be a proxy for hot carcass weight when carcass information is unavailable. Literature shows primarily negative associations between BRDC and final body weight. When assessing risk factors associated with differences in final body weight between cohorts, arrival weight of animals/cohorts should be accounted for, as this could confound the association between BRDC and final body weight. In a 1999 study, researchers found that steer

calves treated for BRDC displayed significantly lower final body weights compared to steers that remained healthy for the duration of the study period (512.9 vs 523.2) (Gardner et al. 1999). Animals that were treated only once for BRDC were not significantly heavier at the end of the feeding period than steers treated > 2 times (Gardner et al. 1999). Researchers in two different studies found similar results: animals requiring treatment demonstrated significantly lower final weights compared to those animals not treated (541.8 vs 545.3 kg; 520 vs 531 kg) (Reinhardt et al., 2009; Schneider et al., 2009a). In all three of these studies, arrival weight was controlled for; in Gardner et al. 2009, it was controlled for in the study design, and in Reinhardt et al. 2009 and Schneider et al. 2009, it was controlled for analytically. These articles show that animals treated for BRDC tend to be sent to harvest at lighter weights than their contemporary group, indicating that BRDC does have a negative effect on animal growth during the finishing phase of production.

Days on feed

Days on feed is the time period from arrival to harvest. When assessing differences in days on feed it is crucial to account for weight of the animal/cohort at arrival because this will have a large influence on the expected number of days an animal/cohort should be at the feedlot. Researchers in South Africa demonstrated that animals that were treated for BRDC were fed an average of 2.7 days more than healthy animals (Thompson et al. 2006). Even larger differences have been shown in steer calves feed in Iowa, where treated animals were on feed an average of five days longer than healthy animals (Faber et al., 1999). Both of these studies assessed days on feed utilizing a multivariable approach that adjusted estimates for arrival weight or age, as well as other covariates. From the limited literature that has looked at differences in days on feed between morbid and healthy animals it appears that morbid animals tend to take longer to finish than healthy animals.

Effect of BRDC on carcass performance

Dating back to the beginning of the nineteenth century, cattle have been marketed on a live weight basis (Mintert, 2003), where the weight of the animal was the only variable that affected the sale price. Over the past decade, the use of grid pricing each individual animal has become more and more popular. The price received for an animal under grid pricing becomes a

function of quality grade, yield grade, and hot carcass weight (Mintert, 2003). These carcass performance measures are now vital in determining the economic return of an animal to the feedlot, and any disease that has a negative effect on these measures could have large economic implications to the feedlot. In recent years, there have been many studies that have assessed the effects of BRDC on carcass performance as part of the main objective or secondary objective.

Quality grade

Quality grade is one of the three factors that make up the base price for many grid pricing programs (Mintert 2003). Quality grade is an evaluation of factors that affect the palatability of meat. The factors that are evaluated are include: amount and distribution of marbling (intramuscular fat) within the ribeye muscle (Longissimus dorsi) at the twelfth rib, carcass maturity, firmness, texture, and color of the muscle (USDA, 1997).

The research regarding the effect of BRDC morbidity on the distribution of marbling within the Longissimus dorsi primarily demonstrates no significant differences between morbid and healthy animals (Jim et al., 1993; Gardner et al., 1999; Roeber et al., 2001; Snowder et al., 2007; Brooks et al., 2009; Garcia et al., 2009). A study in 2009 found heifers receiving one BRDC treatment actually experienced higher marbling scores compared to healthy animals (Montgomery et al., 2009). Two studies showed a significant difference in marbling score between morbid and healthy animals were published in 2009 using data from Iowa feedlots; morbid animals demonstrated lower marbling scores compared to healthy cohorts (Reinhardt et al., 2009; Schneider et al., 2009a). From published literature it is difficult to definitely conclude if BRDC has an impact on marbling score, and if so, how much impact.

The literature regarding the effect of BRDC on overall quality grade is sparse. In a 1999 publication, researchers assessed all components of quality grade (maturity, lean color, and marbling score); finding that animals treated for BRDC tended have more mature carcasses ($P = 0.10$), and significantly better lean color ($P = 0.04$), but no difference in marbling score (Gardner et al., 1999). These cumulative differences in overall quality resulted in a higher percentage of U.S. Choice and Select among healthy animals and a higher percent of morbid animals grading U.S. Standard. However, there was no statistically significant difference in the percent of U.S. Select carcasses between morbid and healthy animals. Animals that were treated multiple times displayed significantly more U.S. Standard carcasses than animals treated < 2 times, but no

difference in marbling score or maturity (Gardner et al., 1999). There appears to be little data demonstrating the effect of BRDC on beef cattle quality grades, although morbid animals seem to have a higher probability of poorer quality grade, which could have economic implications. From the literature available, it is hard to determine whether BRDC has a large impact on beef quality grades; further investigations into the effects of BRDC on overall quality grades need to be performed in order to make definitive conclusions.

Yield grade

Beef carcass yield grade is a major component that determines the base price of a carcass (Mintert 2003). Yield grade is an estimate of the amount of boneless, closely trimmed retail cuts of the high dollar portions of the carcass. Yield grade is a function of fat opposite the ribeye (Longissimus dorsi), percentage of kidney, pelvic, and heart fat (KPH), hot carcass weight, and the area (square inches) of the ribeye (USDA, 1997). This outcome can be reported on a nominal (i.e., yield grade 1 – 5) or continuous scale, and is a crucial part of determining carcass value in a grid based marketing system.

The effect of BRDC treatment on beef yield grades has been mixed, as the effect has been found to differ across the different components determining final yield grade. Researchers assessing all carcass traits used in the calculation of final yield grade found that healthy animals displayed significantly more subcutaneous fat opposite the twelfth rib, more KPH, but not significantly larger ribeyes, thus resulting in significantly higher (i.e. less desirable) USDA yield grades for healthy animals (Snowder et al. 2007; Gardner et al. 1999). These same researchers found similar results for animals treated once compared to > 2 times (Gardner et al. 1999). Others have not found significant differences in yield grades between animals never treated for BRDC and animals treated once, but did find that animals never treated for BRDC had subcutaneous fat and USDA yield grades that were significantly higher compared to animals treated > 1 time (Roeber et al. 2001). Several studies support the previous finding that healthy animals had more (i.e. less desirable) external and KPH fat used to determine USDA yield grade, and any differences found in ribeye area in favor of healthy animals was not enough to result in more desirable USDA yield grades for the healthy animals (Reinhardt et al. 2009; Schneider et al. 2009; Garcia et al. 2009; Montgomery et al. 2009).

Literature has demonstrated that harvested animals never treated for BRDC tend to have less desirable yield grades compared to animals that were treated for BRDC due primarily to increased subcutaneous fat. The magnitude of negative effects of BRDC on other components (e.g. area of ribeye) of yield grade is not large enough to offset the increase in fat cover.

Hot carcass weight

Hot carcass weight (HCW) is an important performance measure to feedlots marketing their animals on a dressed weight or on the grid, as HCW has an influence on the sale price of the animal. It is crucial that carcasses are not too heavy or too light as discounts from the base price will be applied (Ward et al., 2002). Literature supporting the negative effects of BRDC treatment on HCW is abundant, and the majority of results agree that BRDC negatively affects HCW. The magnitude of the effect of BRDC treatment varies between studies, but most have shown significantly negative effects. Many studies have demonstrated the negative effects of BRDC treatment on HCW ranging from 3.0 to 8.6 kg less for previously treated animals (Gardner et al., 1999; Roeber et al., 2001; Snowder et al., 2007; Montgomery et al., 2009; Reinhardt et al., 2009; Schneider et al., 2009a) . It should be noted that Roeber et al. (2001) did not control for arrival weight in their analysis which could confound the relationship between BRDC treatment and HCW. All other studies observing a difference in HCW accounted for arrival weight though experimental design or analysis. Few studies have failed to find differences in HCW between healthy and morbid animals (Garcia et al., 2009). The literature has continually demonstrated a negative association between BRDC and the HCW of animals at harvest. These decreased weights could have substantial economic implications to the feedlots, regardless of how they market their animals.

Economic impact of BRDC

The total economic losses attributed to BRDC including production, preventive, and treatment costs are estimated to approach $4 billion annually (Griffin, 1997). The economic costs associated with prevention and treatment are easy to quantify, but performance losses due to BRDC are more difficult to calculate, as it is hard to differentiate if performance is decreased because of BRDC or that cattle with substandard performance at more apt to become morbid (Smith, 1998).

Even with the high estimated costs associated with BRDC in feedlots, the literature

assessing BRDC costs is relatively rare. The majority of the economic assessments that involve BRDC have come at the end of studies with alternative objectives such as; assessing net returns between metaphylactic/vaccine (Booker et al., 2007; Perrett et al., 2008a; Wildman et al., 2008) or preconditioning programs (Seeger et al., 2008). These study designs make it impossible to evaluate the direct cost associated with BRDC, as they often lack a control group. Therefore, the impact of BRDC treatment cannot be separated from the experimental treatment (i.e. metaphylactic treatment, vaccine, or preconditioning program). A South African study utilized partial budgeting methods to compare two BRDC vaccines using simulation models assessing net profit, and evaluated variables with the greatest influence. The analysis did incorporate treatment costs and mortality, but neither had a large effect on net profit (Gummow and Mapham, 2000). All of the studies above tend to evaluate treatment and performance differences, but never directly quantify the economic differences between morbid and healthy animals.

The most comprehensive assessment of economic outcomes associated with the treatment of BRDC is the Ranch to Rail program in Texas. Since 1993, researchers have been collecting data for producers; allowing producers to learn more about their calf crop and factors that affect production beyond the calf phase of production (McNeill, 2001). Over the duration of collection of this study, BRDC was associated with higher production costs and poorer feedlot performance, in addition to lower USDA quality grades. As a result, animals that remained healthy over the duration of the feeding period earned $92.26 per head more than those animals that receive at least one treatment for BRDC (McNeill et al., 1996). In a 2002 study where researchers assessed the effectiveness of different preconditioning programs by subsequent feedlot performance and carcass evaluation, researchers found that animals that were treated for BRDC once returned $40.64 less, animals treated 2 times $58.35 less, and those > 3 treatments returned $231.93 less than healthy animals (Fulton et al., 2002). Others used gross income figured on a grid price formulation incorporating carcass parameters, and a base price determined by multiplying the average live price over the study period by ADG then multiplied by days on feed (arrival weight adjustment) and found results similar to those above when comparing healthy animals to those treated multiple times, once, twice, and > 3 times ($23.23, $30.15, and $54.01) (Schneider et al., 2009a).

Risk factors for BRDC

Several factors, linked through anecdotal evidence and/or published data, may be associated association with increased incidence of BRDC. One of the first and most comprehensive evaluation of risk factors affecting both morbidity and mortality of feedlot cattle was performed by Martin and colleagues in the late 1970's and early 1980's (Martin et al., 1981a; Martin et al., 1981b; Martin et al., 1982; Martin and Meek, 1986). These large scale field studies were some of the first to quantify the effects of BRDC risk factors (e.g. mixing of cattle, feed, etc.) that had been suspected anecdotally dating back to the 1920's (Jericho, 1979). Since the publication of Martin and colleagues work in the 1980's, researchers have attempted to further quantify the effects of additional risk factors of BRDC.

Association between pre-arrival and arrival health measures on BRDC

Preconditioning

The term preconditioning refers to the comprehensive management system designed to immunize calves against major etiologic agents associated with BRDC, and reduce stressors involved in the beef marketing process (Cole, 1985). The terminology dates back to 1965 when Dr. John Herrick coined the term (Miksch, 1984) . Preconditioning programs are the most encompassing method to prevent BRDC health problems (Speer et al., 2001). Planned management program before shipment to the feedlot can be an effective way to decrease the impact of BRDC (Engelken, 1997). The major components of a preconditioning program involve castration of males, vaccination, a 30 to 40 day weaning prior to shipment, and nutritional management (White and Larson, 2009). The problem with the term "preconditioned" is that it is used very broadly, any cohort that has had one of the above preventive health measures will often be referred to as "preconditioned". This over use of the term has decreased the perceived value of the approach (White and Larson, 2009).

Randomized large scale trials quantifying the effects of preconditioning programs on subsequent feedlot health and performance are rare. The ability of these programs to consistently improve health and performance measures was questioned in the 1980's and 1990's (Cole, 1985; Pritchard and Mendez, 1990). A more recent study involving 500 crossbred steers found that animals that were weaned 45 days prior to shipment and/or vaccinated were

significantly less likely to be treated for BRDC compared to animals coming from auction markets (Step et al., 2008).

Recent economic literature suggests that preconditioning is economically feasible, and feedlots could afford to pay a $14.00 per head premium for preconditioned animals (Dhuyvetter et al., 2005). A feedlot survey found that feedlots expectation of the benefit of preconditioned animals is $5.25/cwt (Avent et al., 2002), but a study published the same year found that the actual gain to the feedlot from preconditioned animals was $8.50 - $9.50/cwt (Roeber and Umberger, 2002). Therefore, the perceived value of preconditioning appears to be undervalued by feedlots.

Due to the horizontal integration of the beef cattle industry, the adoption of preconditioning programs is difficult. For cow-calf producers to utilize a preconditioning program they must receive economic incentive, at the time of calf sale, unless they retain ownership of the animals through the finishing phase. From reviewing the literature, it appears to be important for feedlots to assess the benefits of preconditioned animals within their own production system, and pay premiums for components of preconditioning programs where they realize an economic benefit. Without justly compensating cow-calf producers the industry will continue to be slow to adopt preconditioning programs, and feedlots will fail to consistently see the performance and health benefits consistently.

Metaphylaxis and vaccination at arrival

Preventive medicine programs utilizing mass treatment of animals at arrival with antimicrobials, often called "metaphylaxis," have long displayed a beneficial association with BRDC risk. Some of the earliest studies assessing the effects of mass medication were carried out using a combination of chlortetracycline and sulfamethazine administered in the feed, which was shown to be effective at reducing BRDC risk (Addis et al., 1976). In the early 1980's Lofreen and colleagues displayed the benefits of mass treating highly stressed calves at arrival to the feedlot (Lofgreen et al., 1980; Lofgreen, 1983). In the 1983 study they found that the use of oxytetracycline and sustained-release sulfadimethoxine reduced morbidity from 63.3% in control animals to 7.1% in calves treated upon arrival (Lofgreen, 1983). There have been many studies since Lofgreen's work showing that metaphylactic use of tilmicosin decreases BRDC risk (Galyean et al., 1995; Cusack, 2004; Guthrie et al., 2004). Other long acting antimicrobials like florfenicol and tulathromycin also have been found to be associated with decreased BRDC risk

when administered to animals at arrival to the feedlot (Frank et al., 2002; Rooney et al., 2005; Booker et al., 2007). Studies accurately and consistently demonstrating decreased BRDC incidence from the administration of long acting antimicrobials are critical to feedlots, as the average cost per dose for a 500 pound animal can reach upwards of $17.00 for tulathromycin (Pfizer Animal Health, 2010).

Literature describing the efficacy of BRDC vaccinations used upon arrival to the feedlot has been mixed over the years. In the early 1980's following the Bruce County study, Martin (1983) concluded that vaccines were associated with increased feedlot morbidity and mortality. These conclusions made in 1983 are impossible to extrapolate to the vaccines that are being used in feedlots today as the products have changed substantially in the past 26 years (Fulton, 2009). Today nearly all feedlots vaccinate against some BRDC pathogens upon arrival to the feedlot (BVD-94.4%, IBR-96.9, PI3-86.3%, BRSV-87.4%, Haemophilus somnus-62.1%, and Pasteurella spp.-53.3%) in the hopes of decreasing BRDC morbidity risk (USDA-APHIS, 2000). The majority of current literature compares multivalent vaccine programs, or multiple components to univalent vaccines, but fails to compare these vaccines to negative controls (Schunicht et al., 2003; Perrett et al., 2008b; Wildman et al., 2008). Therefore, it is often difficult to determine for certain, if vaccination at arrival is significantly associated with decreased BRDC incidence.

Association between cattle demographics and BRDC

Origin/commingling

Commingling of cattle has long been suspected of contributing to the increased incidence of BRDC. This is one of the reasons the complex received its original name "Shipping Fever" in the 1920's when animals would be commingled and shipped on rail cars (Jericho, 1979). Comingling of animals can increase stress due to the establishment of social hierarchy, and creates the opportunity of exposure of pathogens to naïve animals (Sanderson et al., 2008). The effect of commingling was first quantified in 1982 by assessing the effect of mixing cattle at arrival to the feedlot on BRDC related death and treatment costs (Martin et al., 1982). They found that pens of animals that had been mixed had higher mortality and treatment costs compared to pens that hadn't been mixed. Other research in the 1980's assessed the effect of the amount of time it took to fill a pen of commingled animals on BRDC risk (Alexander et al.,

1989). Researchers found that BRDC incidence increased as the number of days that it took to fill a pen increased. The expected increase was 7.1 cases of BRDC per 10,000 head-days for every additional day it took to fill the pen (Alexander et al., 1989).

Commingling of animals also takes place at the time of procurement and is common in beef marketing systems. In a study where the majority of animals were commingled prior to shipment, the authors found that mixing of cattle was associated with increased BRDC mortality risk (Ribble et al., 1995b). When comparing groups of cattle commingled and purchased from auction markets to animals that were purchased directly from the ranch, researchers found that commingled animals were 4.9 times as likely to be treated for BRDC, and 6.7 times more likely to die from BRDC (Wilson et al., 1985). More recently research has found that animals that were commingled from multiple sources were two times more likely to be BRDC cases (Sanderson et al. 2008). Differences in adverse BRDC health outcomes by commingling status may be due in part to preventive health programs of animals coming from a direct source, as the final study is the only study that controlled for this effect in their analysis.

Animals arriving from auction markets have been found to increase the risk of adverse health outcomes. Researchers found animals arriving to the feedlot from auction markets experience significantly more BRDC treatments compared to preconditioned animals, and these auction derived animals experienced two times the cumulative BRDC morbidity compared to the preconditioned groups (Roeber et al. 2001). In a recent study, researchers found that animals commingled (i.e. preconditioned and auction derived animals) at arrival to the feedlot experienced BRDC morbidity of 22.6%. Animals coming directly from the ranch experienced BRDC morbidity of 11.1%, whereas those from auction markets were 41.9%; all three origin groups were significantly different from one another (Step et al., 2008). Similarly, animals with unknown history have been found to have higher BRDC morbidity compared to animals of known history (42.63% vs. 15% BRDC risk) (Seeger et al., 2008). This literature demonstrates strong evidence that cohorts with known health status and/or cohorts coming from a single source experience lower adverse BRDC health outcomes compared to those cohorts that have been commingled and/or derived from auction markets.

Arrival weight

Cohorts that enter the feedlot at lighter weights are generally considered to be freshly weaned, stressed animals with a suppressed immune system, and are considered higher risk for

adverse BRDC health outcomes (Lechtenberg et al., 1998). The increased risk of BRDC at arrival for these types of animals is generally thought to be related to age/maturity, source of cattle, previous management, and the amount of commingling prior to entry to the feedlot (Smith et al., 2001). Recently, researchers utilizing data from the USDA's National Animal Health Monitoring System's Feedlot '99 study quantified the effects of risk factors associated with BRDC incidence (Sanderson et al., 2008). These researchers categorized arrival weight into three categories < 250 kg, between 250 and 318 kg, and > 318 kg, and found that the lighter the arrival weight of a cohort resulted in an increased risk of initial BRDC diagnosis. Other studies have found similar results, showing negative association between arrival weight and BRDC health outcomes (Loneragan, 2004; Babcock et al., 2009; Reinhardt et al., 2009).

In an early multivariable analysis of risk factors for BRDC mortality, arrival weight was considered for entry into the model, but was not included in the final model, thus indicating arrival weight was not a significant predictor of BRDC mortality (Martin et al., 1982). Other studies following Martin et al. (1982) found similar results with regard to arrival weight being non-significant in multivariable models. In 1989 researchers found that arrival weight was not significantly associated with BRDC risk in a study of 17,696 head of cattle (Alexander et al. 1989). A case-control study assessing the seroepidemiology of BRDC indirectly assessed the association of arrival weight on BRDC risk by including arrival weight in final models as a proxy for age (considered a nonspecific measure of previous exposure/immunity to pathogens). Results showed that arrival weight was not significantly associated with BRDC risk between cases and controls (Booker et al., 1999). There are some mixed results regarding the association between arrival weight and BRDC health outcomes. The most recent BRDC literature indicates a significant relationship between cohort arrival weights and increased incidence of BRDC health outcomes (Sanderson et al., 2008; Babcock et al., 2009; Reinhardt et al., 2009). Arrival weight plays a role in the magnitude of BRDC incidence within a cohort of cattle, although factors such as preconditioning, source, commingling of cattle, and time of year may vary by weight category potentially confounding the relationship between BRD and arrival weight.

Gender

The literature indicates there are gender differences in BRDC health outcomes. The majority of published literature that has examined gender as a risk factor of adverse BRDC health outcomes has found an association. In a study that utilized data from one feedlot,

researchers found an increase in the incidence of BRDC in steers compared to heifers for the first 18 days on feed (Alexander et al., 1989). This was also the case in a studies conducted by Muggli-Cockett et al. (1992) and Snowder (2006) where both found an increase in BRDC incidence comparing steers to heifers. To our knowledge only one study has looked at cohorts of cattle that were mixed gender (i.e., steers and heifers) (Sanderson et al., 2008). These researchers found that the mixed cohorts had increased BRDC risk compared to both only steer and only heifer cohorts (Sanderson et al., 2008). Mortality has also been found to be differential across genders. Loneragan et al. (2001) studied 121 feedlots in the late 1990's, and found that heifers displayed increased mortality compared to steers, which is different from Cusack et al. (2007) who found steers were at a slightly higher mortality risk. These differing results may be in part due to geographic and demographic differences in study populations. The Cusack et al. (2007) study was done in Australia using cattle purchased during the winter of 2004 and all animals weighed approximately 340 kg. The Loneragan et al. (2001) study population was from multiple United States feedlots across several years. Little research has failed to find an association between gender and adverse BRDC health outcomes (Ribble et al., 1998). Based on published literature it appears that cohorts made up of steers experience increased BRDC risk. This difference may be due to studies not differentiating between male animals castration status at arrival, or there may be a physiologic difference between steers and heifers.

Genetic

The impact of genetics on BRDC risk has been assessed in both the pre-weaning phase and post-weaning phase of cattle production. Low to moderate heritability (range from 0.00 to 0.26) of BRDC resistance has been found in pre-weaned animals (Muggli-Cockett, 1992; Snowder et al., 2005; Schneider et al., 2009b). There also have been reports of significant differences in BRDC risk between breeds during the pre-weaning phase (Muggli-Cockett, 1992; Snowder et al., 2005), but heterozygosity has failed to demonstrate a significant effect on BRDC resistance (Snowder et al., 2005).

The breed of cattle has been found to be significantly associated with BRDC at the feedlot stage of production (Muggli-Cockett, 1992; Snowder, 2006; Cusack et al., 2007; Garcia et al., 2009). The heritability of BRDC resistance of animals entering the feedlot has also been investigated, but results have shown relatively low (0.04 to 0.08) heritability (Snowder, 2006; Snowder et al., 2006; Schneider et al., 2009b). More promising than the heritability research that

has been done previously is the possibility of genomics playing a major role in the management of BRDC, as a physical map of the bovine genome may provide researchers with a tool to aid their search to improve animal health (Snowder, 2009). Recent research is in the beginning stages of discovering quantitative trait loci related to cattle health, which includes BRDC resistance (Casas and Snowder, 2008). The association between BRDC risk and breeds of cattle would suggest that there may be some genetic component to animal health. The research regarding the impact that genetics has on animal health is relatively new, and definitive conclusions on the impact cannot be drawn at this time.

Disposition

Assessing disposition of animals upon arrival to feedlots is a subjective test of how docile or wild an animal is during human-animal interaction (Smith, 2009). Historically, disposition hasn't been found to be associated with adverse health outcomes in feedlots (Smith, 2009). Two studies failed to find significant differences between disposition scores of animals at arrival with any adverse BRDC health outcomes (Faber et al., 1999; Reinhardt et al., 2009). A study published in 2006 did find significant differences in morbidity between disposition scores (Busby et al., 2006). They found that morbidity risk was actually highest in the docile animals, but found no difference between restless and aggressive cattle. Mortality risk between the three disposition categories showed no significant differences (Busby et al. 2006). The majority of research indicates that there is not a strong relationship between animal disposition and adverse health outcomes. This may be due in part to the subjective manner in the way disposition is evaluated, or disposition really may not play a significant role in animal health.

Association between external risk factors and BRDC

Transportation

In the transportation phase of the production process, animals undergo two types of stress: 1) psychological stress (e.g. commingling, restraint, etc.), and 2) physical stress (e.g. hunger, injury, and disease) (Grandin, 1997). There are several studies that have looked at biological markers that are related to stress and/or immunosuppression (Blecha, 1984; Kent and Ewbank, 1986; Murata et al., 1987; Mitchell et al., 1988; Warriss et al., 1995; Mackenzie et al., 1997; Stanger et al., 2005), but relatively few studies that have looked at outcomes that quantify

the effect of transportation length/time of beef cattle on subsequent adverse health outcomes. The results from these studies over the past 20 years have demonstrated mixed results.

Both Cole et al. (1988) and Sanderson et al. (2008) found differences in adverse health outcomes between groups of cattle shipped varying distances. Cole et al. (1988) used 150 feeder calves divided into three treatment groups (control, short-haul, and long-haul). Interestingly, the short-haul group experienced significantly higher morbidity and mortality compared to both the control and long-haul group (Cole et al. 1988). Sanderson et al. (2008) found that longer transport distances were associated with an increase in BRDC morbidity; for every additional 100 miles traveled, BRDC risk went up an average of 10 percent (Sanderson et al. 2008). In contrast, a study published in the 1990's using 45,253 spring-born steers found that the correlation between shipping distance and BRDC mortality was not significant (Ribble et al., 1995c).

The first study (Cole et al. 1988) used a limited study population, and the next two were large retrospective studies (Ribble et al., 1995c; Sanderson et al., 2008). The 2008 by Sanderson et al. looked at BRDC morbidity; whereas, the Ribble et al. (1995c) study assessed BRDC mortality, which may have contributed to the different conclusions. To our knowledge, few feedlots consistently keep electronic data that could be easily used to calculate shipping distance, which may be a reason there are very few published studies evaluating the association between shipping distances and adverse BRDC outcomes.

In addition to distance/length of travel, transport effects also could be influenced by where animals were positioned on the truck. Animal location on the truck could affect factors associated with transport stress such as; vibration, crowding, temperature, and humidity (Swanson and Morrow-Tesch, 2001). Few studies over the past 30 years have assessed the effect of animal location on adverse health outcomes. A study in the 1980's evaluated 965 head of feeder calves shipped from Tennessee to Texas, and found that there were no significant differences in the incidence of BRDC between animals in different trailer compartments (Cole et al., 1988). The most recent publication looking at shipping on adverse health outcomes found that animals that were in the front sections of the truck were more likely to be treated for BRDC compared to animals located in the middle sections of the truck (White et al., 2009). They also found that stocking density of the compartments was significantly associated with increased BRDC risk (higher density resulted in greater risk). The literature regarding animal position on

the trailer is very limited. The most recent research indicates that there are differences in animal health based on where animals are located, and indicate the need for more research in this area.

Weather/Time of entry

In a 1968 issue of the Journal of the American Veterinary Medical Association, an article entitled "Future Requirements for Prevention and Control of Bovine Respiratory Diseases in the United States" suggested that one of the main research area of emphasis should be on how climate is associated with BRDC (Abinanti, 1968). Some 40 years later, the literature is still very sparse regarding the association of weather and BRDC. Baselines of upper and lower critical temperatures have been described in which animals can become stressed because of extreme heat or cold (Fike and Spire, 2006). There has been some work assessing the effect of ambient temperature on calf pneumonia; researchers found that pneumonia mortality occurred more rapidly when temperature was fluctuated in a controlled atmospheric chamber (Stockdale et al., 1979).

Literature associating weather (extreme cold, heat, or other weather events) with BRDC in a field setting is sparse. In a risk factor study utilizing 95 cohorts, containing approximately 18,000 head of cattle from one feedlot, researchers found that a decrease in ambient temperature was negatively associated with BRDC risk (Alexander et al., 1989). In a larger study involving 58,885 spring-born calves from 1985 – 1988, researchers observed that one of the many factors that may have contributed to an increase in BRDC mortality during the fall run was weather (Ribble et al., 1995a). November is when the greatest decrease in average ambient temperature occurred and the most days with measurable precipitation, but they concluded that to quantify these effects multivariable statistical approaches were needed along with more years of data.

Utilizing the same data set, the authors made an attempt to quantify some of the observations made earlier (Ribble et al., 1998). They ran separate models for each year of data in an attempt to predict which truckloads and cohorts would have high BRDC mortality. They found that one weather variable remained in the model (utilizing a manual backward stepwise procedure). The results showed that a drop in ambient temperature around the time of arrival was associated with an increase in BRDC mortality risk. This is opposite of what Alexander et al. (1989) found, but consistent with MacVean et al. (1986) who showed a positive association between the increased incidence of BRDC and daily lows and highs in ambient temperature.

More recently an Australian study found a strong negative association between minimum ambient temperature and daily BRDC incidence. They also found the lower the minimum ambient temperature, and the wider ambient temperature ranges resulted in greater BRDC risk (Cusack et al., 2007). Weather has long been suspected to have an impact on BRDC health outcomes. The studies above indicate that weather or at least temperature may have an association with adverse health outcomes; however, none of these studies attempted to assess the relationship between adverse BRDC health outcomes and weather events. More research is needed to quantify how specific weather events and shifts in temperature over the first several weeks of the feeding phase impact animal health.

Temporal distributions of BRDC

Temporal distributions of disease (e.g., epidemic curves) provide essential information regarding identification and management of feedlot diseases (Booker et al., 2004). Plotting these distributions can provide vital information on the incubation or exposure period, infectivity of the pathogen, and potential route of transmission of the disease (Corbin and Griffin, 2006; Waldner and Campbell, 2006). Feedlot veterinarians have stressed that plotting of temporal distributions should be one of the first steps in a field investigation of feedlot BRDC outbreaks, but to our knowledge this has yet to be applied to managing daily BRDC events (Corbin and Griffin, 2006). Assessing temporal distributions in a quantitative fashion could allow for the development of treatment and control programs customized for specific BRDC patterns.

There are numerous studies showing plots of epidemic curves of BRDC cases for their respective study populations (Woods et al., 1973; Andrews, 1976; Martin, 1983; Wilson et al., 1985; Alexander et al., 1989; Snowder, 2006; Sanderson et al., 2008; Seeger et al., 2008). None of these studies quantify the effect of the timing of BRDC treatment on subsequent performance and health. The common thought in the feedlot industry is that the peak incidence of BRDC is between day 7 and 14 post-arrival (Smith et al., 2001), and that the majority of cases will occur during the first four weeks of the feeding period (Griffin, 1998).

The majority of studies that have looked at the effects of BRDC have done so on a cumulative basis, and not assessed performance and health differences based on when animals are diagnosed and treated for BRDC. The literature that does take into account the timing of BRDC treatment does so by breaking the feeding phase into large periods of time (e.g. weeks,

months, etc). In one of the first studies that attempted to quantify the effect of timing of BRDC events, researchers broke the feeding period into different periods of time based on the evaluation of epidemic curves (Alexander et al. 1989). Therefore, they compared important risk factors for each time period, but did not quantify the overall effect of the timing of BRDC events. Other literature has built on these findings and compared larger periods of time and their effect on performance measures (Faber et al., 1999; Thompson et al., 2006; Snowder et al., 2007). Utilizing feedlot data compiled in Southwest Iowa, researchers determined that animals first treated during different times of the feeding period displayed few differences in performance, but did display differences in subsequent mortality (Faber et al., 1999). The study by Thompson et al. (2006) was done in South Africa where their evaluation of performance was ADG. They split the feeding period was into two periods (< day 35 and > day 35), and found that animals treated for BRDC showed a significant reduction in ADG if treated during the early period compared to healthy animals, but no reduction in ADG if treated post day 35. In the 2007 study by Snowder and colleagues, they broke the feeding period into three periods; early (day 1 to 40), mid (day 41 to 80), and late (day > 80). They determined that animals treated in the late phase of the feeding period exhibited heavier carcasses, more retail product, less fat trim, and heavier bone weight than animals in the early or mid treatment groups. They also found several significant differences in performance based on what period animals were treated compared to healthy animals. In contrast to Thompson et al. (2006), no differences were found in ADG between animals first treated amongst the different time periods (Snowder et al., 2007). Based on the literature reviewed, when BRDC events occur in the feedlot seems to affect subsequent health and performance; however, this literature is sparse. More research needs to be done in this area, as different temporal BRDC patterns of disease events may reflect different population-level disease processes resulting from multiple pathogen, host and environmental interactions.

Conclusion

Bovine respiratory disease complex continues to be the leading cause of disease in feedlots, even though BRDC has been recognized as a problem as early as the 1920's (USDA, 2000; Jericho, 1979). Perhaps part of the reason BRDC research has failed to make major impact is that the epidemiology of the disease in feedlot systems is complex and multiple etiologic, host, and management factors result in variability of disease expression (Cusack et al.,

2003). The result of such variable disease expression has resulted in case definitions that are highly dependent on subjective criteria, and may differ between employees, days of the week, and feedlots (Corbin and Griffin, 2006).

The literature suggests that overall BRDC has a negative impact of feedlot performance measures. There is conclusive evidence that BRDC has a negative effect on ADG, one of the most reported assessments of feedlot animal performance. There is also evidence that adverse BRDC health outcomes negatively affect HCW, but is somewhat inconclusive with regard to quality grade and yield grade. The majority of literature quantifying the effects of BRDC on performance was produced using observational retrospective data, where case definitions were generally based on similar criteria of visual assessment and rectal temperature. The mixed results regarding the effect of BRDC on carcass performance make it hard to quantify the overall economic impact of BRDC. In addition, it is difficult to determine whether performance tends to be decreased in morbid animals because of BRDC or that animals with substandard performance are more apt to become morbid (Smith, 1998). Therefore, a large economic analysis of BRDC in the literature has yet to be completed.

The body of literature quantifying the effects of risk factors prior to feedlot arrival is large, but the majority of studies involved either a limited number of feedlots or geographic locations, or several feedlots and geographical locations, but data aggregated at the feedlot level. There are large gaps of knowledge involving risk factors for BRDC post-arrival, such as weather effects; suggested as an important risk factor dating back to the 1960's (Abinanti, 1968). Other aspects of the epidemiology of BRDC also have been largely absent in the literature. The timing of when BRDC events occur has been advocated as one of the first steps in dealing with a BRDC outbreak, yet the literature regarding the subject is sparse (Corbin and Griffin, 2006). Cumulative measures of disease that are often measured have provided good indications of the risk factors for, and impacts of BRDC, yet the associations are based on the magnitude of disease burden within a cohort while ignoring potentially important temporal patterns of BRDC occurrence (Sanderson et al., 2008). In moving forward with BRDC research, investigators need to apply knowledge gained about risk factors for BRDC and continue to quantify these effects, while constructing models that accurately predict disease patterns and cumulative disease burden. This would allow for real-time evidence-based decisions in commercial feedlots, and

effective forecasting and surveillance methods to improve BRDC management and enhance feedlot cattle health, performance, and welfare.

References

Abinanti, F.R., 1968. Future requirements for prevention and control of bovine respiratory diseases in the United States. J.A.M.A. 152, 934-937.

Addis, D.G., Lofgreen, G.P., Clark, J.G., Dunbar, J.R., Adams, C., Cress, F.D., 1976. Preventive medication for feedlot replacement calves. California Agr. 30.

Alexander, B.H., MacVean, D.W., Salman, M.D., 1989. Risk factors for lower respiratory tract disease in a cohort of feedlot cattle. J. Am. Vet. Med. Assoc. 195, 207-211.

Andrews, A.H., 1976. Factors affecting the incidence of pneumonia in growing bulls. Vet. Record 98, 146-149.

Apley, M., 2006. Bovine respiratory disease: pathogenesis, clinical signs, and treatment in lightweight calves. Vet. Clin. North Am. Food Anim. Pract. 22, 399-411.

Avent, R.K., Ward, C.E., Lalman, D.L., 2002. Asymmetric value of preconditioning programs for feeder cattle. In, Western Agricultural Economics Association Annual Meeting, Long Beach, CA.

Babcock, A.H., White, B.J., Dritz, S.S., Thomson, D.U., Renter, D.G., 2009. Feedlot health and performance effects associated with the timing of respiratory disease treatment. J. Anim. Sci. 87, 314-327.

Babiuk, L.A., Acres, S.D., 1984. Models for bovine respiratory disease. In, Proceedings of the North American Symposium on bovine respiratory disease, College Station, TX.

Bateman, K.G., Martin, S.W., Shewen, P.E., Menzies, P.I., 1990. An evaluation of antimicrobial therapy for undifferentiated bovine respiratory disease. Can. Vet. J. 31, 689-696.

Blecha, F., Boyles SL, Riley JG, 1984. Shipping suppresses lymphocyte blastogenic responses in angus and brahman x angus feeder calves. . J. Anim. Sci. 59, 576-583.

Booker, C.W., Abutarbush, S.M., Schunicht, O.C., Jim, G.K., Perrett, T., Wildman, B.K., Guichon, P.T., Pittman, T.J., Jones, C., Pollock, C.M., 2007. Evaluation of the efficacy of tulathromycin as a metaphylactic antimicrobial in feedlot calves. Vet. Ther. 8, 183-200.

Booker, C.W., Guichon, P.T., Jim, G.K., Schunicht, O.C., Harland, R.J., Morley, P.S., 1999. Seroepidemiology of undifferentiated fever in feedlot calves in western Canada. Can. Vet. J. 40, 40-48.

Booker, C.W., Loneragan, G.H., Guichon, P.T., Kee, J.G., Schunicht, O.C., Wildman, B.K., Pittman, T.J., Fenton, R.K., Janzen, E.D., Perrett, T., 2004. Practical Application of Epidemiology in Veterinary Herd Health/production Medicine. In, AABP Proceedings, pp. 59-62.

Brooks, K., Raper, K.C., Ward, C.E., Holland, B.P., Krehbiel, C., 2009. Economic effects of bovine respiratory disease on feedlot cattle during backgrounding and finishing phases. Southern Agricultural Economics Association Annual Meeting. Atlanta, Georgia.

Busby, D., Strohbehn, D., Beedle, P., King, M., 2006. Effect of disposition on feedlot gain and quality grade. Iowa State University Animal Industry Report. Iowa State University, Ames, IA.

Callan, R.J., Garry, F.B., 2002. Biosecurity and bovine respiratory disease. Vet. Clin. North Am. Food Anim. Pract. 18, 57-77.

Casas, E., Snowder, G.D., 2008. A putative quantitative trait locus on chromosome 20 associated with bovine pathogenic disease incidence. J. Anim. Sci. 86, 2455-2460.

Cole, N.A., 1985. Preconditioning calves for the feedlot. Vet. Clin. North Am. Food Anim. Pract. 1, 401.

Cole, N.A., Camp, T.H., Rowe, L.D., Jr., Stevens, D.G., Hutcheson, D.P., 1988. Effect of transport on feeder calves. Am. J. Vet. Res. 49, 178-183.

Cole, N.A., McLaren, J.B., Irwin, M.R., 1979. Influence of pretransit feeding regimen and posttransit B-vitamin supplementation on stressed feeder steers. J. Anim. Sci. 49, 310-317.

Corbin, M.J., Griffin, D., 2006. Assessing performance of feedlot operations using epidemiology. Vet. Clin. North Am. Food Anim. Pract. 22, 35-51.

Cusack, P., McMeniman, N., Lean, I., 2003. The medicine and epidemiology of bovine respiratory disease in feedlots. Aust. Vet. J. 81, 480-487.

Cusack, P.M., McMeniman, N.P., Lean, I.J., 2007. Feedlot entry characteristics and climate: their relationship with cattle growth rate, bovine respiratory disease and mortality. Aust. Vet. J. 85, 311-316.

Cusack, P.M.V., 2004. Effect of mass medication and antibiotics at feedlot entry on the health and growth rate of cattle destined for the Australian domestic market. Aust. Vet. J. 82, 154-156.

Dabo, S.M., Taylor, J.D., Confer, A.W., 2007. Pasteurella multocida and bovine respiratory disease. Anim. Health Res. Rev. 8, 129-150.

Dhuyvetter, K.C., Bryant, A.M., Blasi, D.A., 2005. Case Study: Preconditioning Beef Calves: Are Expected Premiums Sufficient to Justify the Practice? Prof. Anim. Sci. 21, 502-514.

Edwards, A., 1996. Respiratory Diseases of Feedlot Cattle in Central USA. Bov. Pract. 30, 5-7.

Engelken, T.J., 1997. Preventative programs for respiratory disease in cow/calf operations. Vet. Clin. North Am. Food Anim. Pract. 13, 647-660.

Faber, R., Hartwig, N., Busby, D., BreDahl, R., 1999. The costs and predictive factors of bovine respiratory disease in standardized steer tests. In: Strohbehn DR, ed. Beef Research Report. Animal science leaflet R1648. Ames, Iowa: Iowa State University.

Fike, K., Spire, M.F., 2006. Transportation of cattle. Vet. Clin. North Am. Food Anim. Pract. 22, 305-320.

Frank, G.H., Briggs, R.E., 1992. Colonization of the tonsils of calves with *Pasteurella haemolytica*. Am. J. Vet. Res. 53, 481-484.

Frank, G.H., Briggs, R.E., Duff, G.C., Loan, R.W., Purdy, C.W., 2002. Effects of vaccination prior to transit and administration of florfenicol at time of arrival in a feedlot on the health of transported calves and detection of Mannheimia haemolytica in nasal secretions. Am. J. Vet. Res. 63, 251-256.

Frank, G.H., Briggs, R.E., Zehr, E.S., 1995. Colonization of the tonsils and nasopharynx of calves by rifampicin-resistant *Pasteurella haemolytica* and its inhibition by vaccination. Am. J. Vet. Res. 56, 866-869.

Fulton, R.W., 2009. Bovine respiratory disease research (1983-2009). Anim. Health Res. Rev. 10, 131-139.

Fulton, R.W., Cook, B.J., Step, D.L., Confer, A.W., Saliki, J.T., Payton, M.E., Burge, L.J., Welsh, R.D., Blood, K.S., 2002. Evaluation of health status of calves and the impact on feedlot performance: assessment of a retained ownership program for postweaning calves. Can. J. Vet. Res. 66, 173-180.

Galyean, M.L., Gunter, S.A., Malcolm-Callis, K.J., 1995. Effects of arrival medication with tilmicosin phosphate on health and performance of newly received beef cattle. J. Anim. Sci. 73, 1219-1226.

Galyean, M.L., Perino, L.J., Duff, G.C., 1999. Interaction of cattle health/immunity and nutrition. J. Anim. Sci. 77, 1120-1134.

Garcia, M.D., Thallman, R.M., Wheeler, T.L., Shackelford, S.D., Casas, E., 2009. Effect of bovine respiratory disease and overall pathogenic disease incidence on carcass traits. J. Anim. Sci. 88, 491-496.

Gardner, B.A., Dolezal, H.G., Bryant, L.K., Owens, F.N., Smith, R.A., 1999. Health of finishing steers: effects on performance, carcass traits, and meat tenderness. J. Anim. Sci. 77, 3168-3175.

Grandin, T., 1997. Assessment of stress during handling and transport. J. Anim. Sci. 75, 249-257.

Griffin, D., 1997. Economic impact associated with respiratory disease in beef cattle Vet. Clin. North Am. Food Anim. Pract. 13, 367-377.

Griffin, D., 1998. Feedlot Diseases. Vet. Clin. North Am. Food Anim. Pract. 14, 199-231.

Griffin, D., Perino, L., Wittum, T., 1995. Feedlot Respiratory Disease: Cost, Value of Preventives and Intervention. In: Williams, E.I. (Ed.), American Association of Bovine Practitioners, Pittsburgh, PA, pp. 157-160.

Gummow, B., Mapham, P.H., 2000. A stochastic partial-budget analysis of an experimental Pasteurella haemolytica feedlot vaccine trial. Prev. Vet. Med. 43, 29-42.

Guthrie, C.A., Rogers, K.C., Christmas, R.A., Vogel, G.J., Laudert, S.B., Mechor, G.D., 2004. Efficacy of metaphylactic tilmicosin for controlling bovine respiratory disease in high-risk northern feeder calves. Bov. Pract. 38, 46-53.

Jacobson, L.H., Cook, C.J., 1998. Partitioning psychological and physical sources of transport-related stress in young cattle. Vet. J. 155, 205-208.

Jericho, K.W., 1979. Update on Pasteurellosis. Can. Vet. J. 20, 333-335.

Jim, G.K., Booker, C.W., Ribble, C.S., Guichon, P.T., Thorlakson, B.E., 1993. A field investigation of the economic impact of respiratory disease in feedlot calves. Can. Vet. J. 34, 668-673.

Johnson, J.C., Bryson, W.L., Barringer, S., Hunsaker, B.D., 2008. Evaluation of on-arrival versus prompted metaphylaxis regimes using Ceftiofur Crystalline Free Acid for feedlot heifers at risk of developing bovine respiratory disease. Vet. Ther. 9, 53-62.

Kapil, S., Basaraba, R.J., 1997. Infectious Bovine Rhinotracheitis, Parainfluenze-3, and Respiratory Coronavirus. Vet. Clin. Food Anim. 13, 455-469.

Kelly, A.P., Janzen, E.D., 1986. A Review of morbidity and mortality rates and disease occurance in North American feedlot cattle. Can. Vet. J. 27, 496-500.

Kent, J.E., Ewbank, R., 1986. The effect of road transportation on the blood constituents and behaviour of calves. II. one to three weeks old. The British Vet. J. 142, 131-140.

Lechtenberg, K.F., Smith, R.A., Stokka, G.L., 1998. Feedlot health and management. Vet. Clin. North Am. Food Anim. Pract. 14, 177-197.

Lillie, L.E., 1974. The bovine respiratory disease complex. Can. Vet. J. 14, 233-242.

Lofgreen, G.P., 1983. Mass medication in reducing shipping fever-bovine respiratory disease complex in highly stressed calves. J. Anim. Sci. 56, 529-536.

Lofgreen, G.P., Stinocher, L.H., Kiesling, H.E., 1980. Effects of dietary energy, free choice alfalfa hay and mass medication on calves subjected to marketing and shipping stresses. J. Anim. Sci. 50, 590-596.

Loneragan, G.H., 2004. Feedlot mortalities: epidemiology, trends, classification. In, Academy of Veterinary Consultants Summer Meeting, Colorado Springs, CO.

Loneragan, G.H., Dargatz, D.A., Morley, P.S., Smith, M.A., 2001. Trends in mortality ratios among cattle in US feedlots. J. Am. Vet. Med. Assoc. 219, 1122-1127.

Macartney, J.E., Bateman, K.G., Ribble, C.S., 2003. Health performance of feeder calves sold at conventional auctions versus special auctions of vaccinated or conditioned calves in Ontario. J. Am. Vet. Med. Assoc. 223, 677-683.

Mackenzie, A.M., Drennan, M., Rowan, T.G., Dixon, J.B., Carter, S.D., 1997. Effect of transportation and weaning on humoral immune responses of calves. Res. Vet. Sci. 63, 227-230.

MacVean, D.W., Franzen, D.K., Keefe, T.J., Bennett, B.W., 1986. Airborne particle concentration and meteorologic conditions associated with pneumonia incidence in feedlot cattle. Am. J. Vet. Res. 47, 2676-2682.

Martin, S.W., 1983. Factors influencing morbidity and mortality in feedlot calves in Ontario. Vet. Clin. North Am. Large Anim. Pract. 5, 73.

Martin, S.W., Bateman, K.G., Shewen, P.E., Rosendal, S., Bohac, J.E., 1989. The frequency, distribution and effects of antibodies, to seven putative respiratory pathogens, on respiratory disease and weight gain in feedlot calves in Ontario. Can. J. Vet. Res. 53, 355-362.

Martin, S.W., Bohac, J.G., 1986. The association between serological titers in infectious bovine rhinotracheitis virus, bovine virus diarrhea virus, parainfluenza-3 virus, respiratory syncytial virus and treatment for respiratory disease in Ontario feedlot calves. Can. J. Vet. Res. 50, 351-358.

Martin, S.W., Meek, A.H., 1986. A path model of factors influencing morbidity and mortality in Ontario feedlot calves. Can. J. Vet. Res. 50, 15-22.

Martin, S.W., Meek, A.H., Davis, D.G., Johnson, J.A., Curtis, R.A., 1981a. Factors associated with morbidity and mortality in feedlot calves: the Bruce County beef project, year two. Can. J. Comp. Med. 45, 103-112.

Martin, S.W., Meek, A.H., Davis, D.G., Johnson, J.A., Curtis, R.A., 1982. Factors associated with mortality and treatment costs in feedlot calves: the Bruce County Beef Project, years 1978, 1979, 1980. Can. J. Comp. Med. 46, 341-349.

Martin, S.W., Meek, A.H., Feltmate, T.E., Curtk, R.A., Johnson, J.A., Davis, D.G., 1981b. Factors Related to Sickness and Death in Feedlot Calves. Bov. Prac. 13, 32-36.

Martin, S.W., Meek, A.H., Willeberg, P., 1987. Veterinary Epidemiology principles and methods. Iowa State University Press Ames, IA.

McNeill, J.W., 2001. 2000-2001 Texas A&M Ranch to Rail - North/South Summary Report ASWeb-O84. Texas A&M.

McNeill, J.W., Paschal, J.C., McNeill, M.S., Morgan, W.W., 1996. Effect of morbidity on performance and profitability of feedlot steers. J. Anim. Sci. 72(Suppl 1):, 135.

Miksch, D., 1984. Preconditioning programs for feeder cattle. Mod. Vet. Pract. 65, 341-344.

Mintert, J. 2003. Beef feedlot industry. Vet. Clin. North Am. Food Anim. Pract. 19, 387-395.

Mitchell, G., Hattingh, J., Ganhao, M., 1988. Stress in cattle assessed after handling, after transport and after slaughter. Vet. Rec. 123, 201-205.

Montgomery, S.P., Sindt, J.J., Greenquist, M.A., Miller, W.F., Pike, J.N., Loe, E.R., Sulpizio, M.J., Drouillard, J.S., 2009. Plasma metabolites of receiving heifers and the relationship between apparent bovine respiratory disease, body weight gain, and carcass characteristics. J. Anim. Sci. 87, 328-333.

Morck, D.W., Merrill, J.K., Thorlakson, B.E., Olson, M.E., Tonkinson, L.V., Costerton, J.W., 1993. Prophylactic efficacy of tilmicosin for bovine respiratory tract disease. J. Am. Vet. Med. Assoc. 202, 273-277.

Mosier, D.A., 1989. The evolution of vaccines for bovine pneumonic pasteurellosis. Res. Vet. Sci. 47, 1-10.

Muggli-Cockett, N.E., 1992. Genetic Analysis of Bovine Respiratory Disease in Beef Calves During the First Year of Life. J. Anim. Sci. 70, 2013-2019.

Murata, H., Takahashi, H., Matsumoto, H., 1987. The effects of road transportation on peripheral blood lymphocyte subpopulations, lymphocyte blastogenesis and neutrophil function in calves. The British Vet. J. 143, 166-174.

Perino, L.J., Hunsaker, B.D., 1997. A review of bovine respiratory disease vaccine field efficacy. Bov. Prac. 1-20.

Perrett, T., Abutarbush, S.M., Wildman, B.K., Fuchs, M.T., Schunicht, O.C., Pollock, C.M., Fenton, R.K., Jim, G.K., Guichon, P.T., Booker, C.W., Berg, J., Roder, J., Spire, M., 2008a. A comparison of florfenicol and tulathromycine for the treatment of undifferentiated Fever in feedlot calves. Vet. Ther. 9, 128-140.

Perrett, T., Wildman, B.K., Abutarbush, S.M., Pittman, T.J., Jones, C., Pollock, C.M., Schunicht, O.C., Guichon, P.T., Jim, G.K., Booker, C.W., 2008b. A comparison of two *Mannheimia haemolytica* immunization programs in feedlot at high risk of developing undifferentiated fever/bovine respiratory disease. Bov. Pract. 42, 64-75.

Pfizer Animal Health, 2010. http://www.draxxin.com/Draxxin_StudiesAssumptions.aspx

Pritchard, R.H., Mendez, J.K., 1990. Effects of preconditioning on pre- and post-shipment performance of feeder calves. J. Anim. Sci. 68, 28-34.

Reinhardt, C.D., Busby, W.D., Corah, L.R., 2009. Relationship of various incoming cattle traits with feedlot performance and carcass traits. J. Anim. Sci. 87, 3030-3042.

Ribble, C.S., Meek, A.H., Janzen, E.D., Guichon, P.T., Jim, G.K., 1995a. Effect of time of year, weather, and the pattern of auction market sales on fatal fibrinous pneumonia (shipping fever) in calves in a large feedlot in Alberta (1985-1988). Can. J. Vet. Res. 59, 167-172.

Ribble, C.S., Meek, A.H., Shewen, P.E., Guichon, P.T., Jim, G.K., 1995b. Effect of pretransit mixing on fatal fibrinous pneumonia in calves. J. Am. Vet. Med. Assoc. 207, 616-619.

Ribble, C.S., Meek, A.H., Shewen, P.E., Jim, G.K., Guichon, P.T., 1995c. Effect of transportation on fatal fibrinous pneumonia and shrinkage in calves arriving at a large feedlot. J. Am. Vet. Med. Assoc. 207, 612-615.

Ribble, C.S., Meek, A.H., Shoukri, M.M., Guichon, P.T., Jim, G.K., 1998. Risk factors associated with fatal fibrinous pneumonia (Shipping Fever) in feedlot calves. In, Proc Am Assoc Bov Pract, pp. 104-109.

Rice, J.A., Carrasco-Medina, L., Hodgins, D.C., Shewen, P.E., 2007. Mannheimia haemolytica and bovine respiratory disease. Animal health research reviews / Conference of Research Workers in Animal Diseases 8, 117-128.

Roeber, D.L., Speer, N.C., Gentry, J.G., Tatum, J.D., Smith, C.D., Whittier, J.C., Jones, G.F., Belk, K.E., Smith, G.C., 2001. Feeder cattle health management: Effects on morbidity rates, feedlot performance, carcass characteristics, and beef palatability. Prof. Anim. Sci. 17, 39-44.

Roeber, D.L., Umberger, W.J., 2002. The value of preconditioning programs in beef production systems. In, Western Agricultural Economics Association Annual Meeting, Long Beach, CA.

Rooney, K.A., Nutsch, R.G., Skogerboe, T.L., Weigel, D.J., Gajewski, K., Kilgore, W.R., 2005. Efficacy of tulathromycin compared with tilmicosin and florfenicol for the control of respiratory disease in cattle at high risk of developing bovine respiratory disease. Vet. Ther. 6, 154-166.

Sanderson, M.W., Dargatz, D.A., Wagner, B.A., 2008. Risk factors for initial respiratory disease in United States' feedlots based on producer-collected daily morbidity counts. Can. Vet. J. 49, 373-378.

Schneider, M.J., Tait, R.G., Jr., Busby, W.D., Reecy, J.M., 2009a. An evaluation of bovine respiratory disease complex in feedlot cattle: Impact on performance and carcass traits using treatment records and lung lesion scores. J. Anim. Sci. 87, 1821-1827.

Schneider, M.J., Tait, R.G., Jr., Ruble, M.V., Busby, W.D., Reecy, J.M., 2009b. Evaluation of fixed sources of variation and estimation of genetic parameters for incidence of bovine respiratory disease in prewean calves and feedlot cattle. J. Anim. Sci. 88, 1220-1228.

Schunicht, O.C., Booker, C.W., Jim, G.K., Guichon, P.T., Wildman, B.K., Hill, B.W., 2003. Comparison of a multivalent viral vaccine program versus a univalent viral vaccine program on animal health, feedlot performance, and carcass characteristics of feedlot calves. Can. Vet. J. 44, 43-50.

Seeger, J.T., Grotelueschen, D.M., Stokka, G.L., Sides, G.E., 2008. Comparison of feedlot health, nutritional performance, carcass characteristics and economic value of unweaned beef calves with an unknown health history and weaned beef calves receiving various herd-of-origin health protocols. Bov. Pract. 42, 27-39.

Smith, R.A., 1998. Impact of disease on feedlot performance: a review. J Anim. Sci 76, 272-274.

Smith, R.A., 2009. North American cattle marketing and bovine respiratory disease (BRD). Animal health research reviews. 10, 105-108.

Smith, R.A., Stokka, G.L., Radostits, O.M., D.D.Griffin, 2001. Health and Production Management in Beef Feedlots. In: Radostits, O.M. (Ed.), Herd Health: Food Animal Production Medicine. W.B. Saunders Company, Philadelphia, pp. 581-633.

Snowder, G., 2009. Genetics, environment and bovine respiratory disease. Animal health research reviews. 10, 117-119.

Snowder, G.D., 2006. Bovine respiratory disease in feedlot cattle: Environmental, genetic, and economic factors. J. Anim. Sci. 84, 1999-2008.

Snowder, G.D., Van Vleck, L.D., Cundiff, L.V., Bennett, G.L., 2005. Influence of breed, heterozygosity, and disease incidence on estimates of variance components of respiratory disease in preweaned beef calves. J. Anim. Sci. 83, 1247-1261.

Snowder, G.D., Van Vleck, L.D., Cundiff, L.V., Bennett, G.L., 2006. Bovine respiratory disease in feedlot cattle: Environmental, genetic, and economic factors. J. Anim. Sci. 84, 1999-20008.

Snowder, G.D., Van Vleck, L.D., Cundiff, L.V., Bennett, G.L., Koohmaraie, M., Dikeman, M.E., 2007. Bovine respiratory disease in feedlot cattle: phenotypic, environmental, and genetic correlations with growth, carcass, and longissimus muscle palatability traits. J. Anim. Sci. 85, 1885-1892.

Speer, N.C., Young, C., Roeber, D., 2001. The importance of preventing bovine respiratory disease: A beef industry review. Bov. Pract. 35, 189-196.

Stanger, K.J., Ketheesan, N., Parker, A.J., Coleman, C.J., Lazzaroni, S.M., Fitzpatrick, L.A., 2005. The effect of transportation on the immune status of Bos indicus steers. J. Anim. Sci. 83, 2632-2636.

Step, D.L., Krehbiel, C.R., DePra, H.A., Cranston, J.J., Fulton, R.W., Kirkpatrick, J.G., Gill, D.R., Payton, M.E., Montelongo, M.A., Confer, A.W., 2008. Effects of commingling beef calves from different sources and weaning protocols during a 42-day receiving period on performance and bovine respiratory disease. J. Anim. Sci., 86, 3146-3158.

Stockdale, P., Jericho, K.W.F., Yates, W.D.G., 1979. Experimental bovine pneumonic pasteurellosis. II. Can. J. Comp. Med. 43, 272-279.

Swanson, J.C., Morrow-Tesch, J., 2001. Cattle transport: Historical, research, and future perspectives. J. Anim. Sci. 79(E. Suppl.), E109-E109.

Thompson, P.N., Stone, A., Schultheiss, W.A., 2006. Use of treatment records and lung lesion scoring to estimate the effect of respiratory disease on growth during early and late finishing periods in South African feedlot cattle. J. Anim. Sci. 84, 488-498.

USDA-APHIS, 2000. Vaccination of cattle against respiratory disease pathogens in U.S. feedlots. In: USDA (Ed.).

USDA, 1997. United States Standards for Grades of Carcass Beef. In: United States Department of Agriculture, A.M.S. (Ed.), Washington, DC.

USDA, 2000. Part III: Health Management and Biosecurity in U.S. Feedlots, 1999. In: USDA:APHIS:VS (Ed.) National Animal Health Monitoring System, Fort Collins, CO.

Van Donkersgoed, J., 1992. Meta-analysis of field trials of antimicrobial mass medication for prophylaxis of bovine respiratory disease in feedlot cattle. Can. Vet. J. 33, 786-795.

Vogel, G.J., Parrott, C., 1994. Mortality survey in feedyards: The incldence of death from digestive, respiratory, and other causes in feedyards on the Great Plains. Food Anim. Comp. 16, 227-234.

Waldner, C.L., Campbell, J.R., 2006. Disease outbreak investigation in food animal practice. Vet. Clin. North Am. Food Anim. Pract. 22, 75-101.

Ward, C.E., Schroeder, T.C., Feuz, D.M., 2002. Grid Base Prices and Premiums-Discounts Over Time. Managing for Today's Cattle Market and Beyond. Kansas State University, Manhattan, Kansas.

Warriss, P.D., Brown, S.N., Knowles, T.G., Kestin, S.C., Edwards, J.E., Dolan, S.K., Phillips, A.J., 1995. Effects on cattle of transport by road for up to 15 hours. Vet. Rec. 136, 319-323.

White, B.J., Blasi, D., Vogel, L.C., Epp, M., 2009. Associations of beef calf wellness and body weight gain with internal location in a truck during transportation. J. Anim Sci. 87, 4143-4150.

White, B.J., Larson, R.L., 2009. Preconditioned calves in the feedyard. In: Anderson, D.E., Rings, D.M. (Eds.), Food animal practice. Saunders Elsevier, St. Louis, MO, pp. 628-632.

Wildman, B.K., Perrett, T., Abutarbush, S.M., Guichon, P.T., Pittman, T.J., Booker, C.W., Schunicht, O.C., Fenton, R.K., Jim, G.K., 2008. A comparison of 2 vaccination programs in feedlot calves at ultra-high risk of developing undifferentiated fever/bovine respiratory disease. Can. Vet. J. 49, 463-472.

Wilson, S.H., Church, T.L., Acres, S.D., 1985. The Influence of Feedlot Management on an Outbreak of Bovine Respiratory Disease. Can. Vet. J. 26, 335-341.

Wittum, T.E., Perino, L.J., 1995. Passive immune status at postpartum hour 24 and long-term health and performance of calves. Am. J. Vet. Res. 56, 1149-1154.

Wittum, T.E., Woollen, N.E., Perino, L.J., Littledike, E.T., 1996. Relationships among treatment for respiratory tract disease, pulmonary lesions evident at slaughter, and rate of weight gain in feedlot cattle. J. Am. Vet. Med. Assoc. 209, 814-818.

Woods, G.T., Mansfield, M.E., Webb, R.J., 1973. A three year comparison of acute respiratory disease, shrink and weight gain in preconditioned and non-preconditioned Illinois beef calves sold at the same auction and mixed in a feedlot. Can. J. Comp. Med. 37, 249.

CHAPTER 2 - Feedlot health and performance effects associated with the timing of respiratory disease

A. H. Babcock[*,†], B. J. White[2,*], S. S. Dritz[†], D. U. Thomson[*], and D. G. Renter[†]

[*]Department of Clinical Sciences, Kansas State University, Manhattan, KS, 66506

[†]Department of Diagnostic Medicine/Pathobiology

Kansas State University, Manhattan, KS 66506

Abstract

Generalized linear mixed models were developed using retrospective feedlot data collected on individually treated cattle (n = 31,131) to determine whether cattle performance and health outcomes in feedlot cattle were associated with timing of treatment for bovine respiratory disease (BRD) during the feeding phase. Cattle that died at any point during the feeding phase were removed from the analysis. Information on individual animal performance (ADG, HCW, quality grade, yield grade) and health outcomes (treatments) were incorporated into an economic model that generated a standardized net return estimate for each animal. Prices were standardized to minimize variation between economic outcomes due to market conditions allowing direct comparisons of health and performance effects between animals. While controlling for gender, risk code, and arrival weight class, potential associations between net returns, and the timing of BRD identification were investigated using 2 categorical variables created to measure time: 1) weeks on feed at initial BRD treatment (WKFA), and 2) weeks from BRD treatment to harvest (WKTH). The first model using net return as the outcome identified an interaction between WKFA and animal arrival weight. Cattle with arrival BW between 227 and 272 kg (5WT) and 273 and 318 kg (6WT) displayed lower net returns ($P < 0.05$) if treated during wk 1 as compared to subsequent weeks in the first month of the feeding phase. The cattle

with BW between 319-363 kg (7WT) and 364 and 408 kg (8WT) exhibited lower net returns (P < 0.05) if treated during the later weeks of the feeding phase compared to earlier in the feeding phase. The number of times cattle were treated contributed to variation in net returns for the 5WT and 6WT cattle. For the 7WT and 8WT cattle, HCW was the main factor contributing to lower net returns when cattle were treated late in the feeding phase. The second model identified an interaction between WKTH and arrival weight. The 4WT, 5WT, 6WT, 7WT, and 8WT cattle all exhibited lower net returns (P < 0.05) when cattle were on feed fewer weeks from BRD treatment to harvest. Cattle with more weeks on feed between BRD treatment and harvest had greater HCW, lower ADG, and more total treatments compared to cattle treated closer to harvest. This research indicates that timing of initial BRD treatment is associated with performance and health outcomes.

Introduction

Bovine Respiratory Disease (BRD) is the most common and economically detrimental disease of cattle during the post-weaning phase, causing approximately 75% of morbidity and over 50% of mortality in feedlots (Edwards, 1996; Smith, 1998). Respiratory disease costs the beef industry more than $690 million annually (National Agricultural Statistics Service, 2006). Literature clearly supports the negative impacts of BRD on cattle performance and economics (Gardner et al., 1999; Martin et al., 1989), yet research evaluating the effect of disease timing is rare. A recent study compared early and late BRD in 2 South African feedlots and found that cattle treated for BRD early in the feeding phase (< d 35) experienced a decrease of 0.22 kg in ADG compared to cattle without disease, whereas cattle treated late in the feeding phase (> d 35) experience no significant reduction in ADG relative to untreated cattle (Thompson et al., 2006). These findings suggest that the time of treatment for BRD affects cattle performance.

Our study is unique as we used individual animal data from a U.S. feedlot to evaluate the effect of the timing of initial BRD treatment on cattle performance. Our hypothesis was that the time of identification and treatment of BRD during the feeding phase impacts performance outcomes. This was tested through statistical analyses that considered time relative to either arrival or harvest. Multiple outcomes could be used to compare biological effects of disease timing, but we initially utilized a standardized net return measure as the outcome variable to incorporate all available individual animal performance and health data. The net returns figure is

a screening metric to identify differences that could be due to multiple biological factors. Our objectives were to determine whether cattle performance and health were associated with the number of weeks from arrival to initial BRD treatment or the number of weeks from BRD treatment to harvest.

Materials and methods

Data were acquired from a Midwestern U.S. feedlot and included cattle harvested between January 1, 2001 and February 2, 2006. The data set consisted of individual animal performance, health, and carcass records of 37,078 cattle treated for respiratory disease using the standard treatment protocol designed by the consulting veterinarian. Only cattle identified and treated for respiratory disease before 100 d after arrival were included in the data set (n = 31,131). Data for all cattle included: individual identification number, lot, gender, pen, risk code (as assigned by feedlot), arrival date, arrival weight, morbidity data (number of times treated, date(s) treated, and diagnosis), mortality data (yes or no, date), harvest date, HCW, quality grade (QG), backfat, LM area, yield grade, as well as KPH. Gender, pen, and risk code were recorded on a pen basis, and all other variables were collected and reported on individual animals. Risk codes were assigned by feedlot personnel, which classified each incoming lot of cattle as to expected health risk based on cattle history, including weaning status, and types of preconditioning programs. Diagnosis at initial treatment was determined and recorded by feedlot personnel responsible for daily health management of the cattle. Cases were identified based on standard industry procedures including evaluation of animal appearance, demeanor, and body temperature.

Data were imported into Insightful Miner (Version 7, Insightful Corp., Seattle, WA), where each record was validated and new variables were created for the analysis. The validation procedure eliminated records if performance or carcass data were incomplete, days on feed at first treatment was past 100 d, or if diagnosis at initial treatment was not BRD. Data also were evaluated for unrealistic (i.e. negative number of days between treatment and harvest) or indeterminable values (lot gender marked as mixed), data meeting these criteria were removed from the analysis. Heifers with arrival weight greater than 454 kg were removed from the data set as historical prices for these cattle were not available. Records for cattle that were treated for

BRD and died before harvest were removed from the economic analysis comparing cattle performance. The criteria above resulted in the elimination of 5,947 animals.

New variables were created for the analysis using the existing data. Calculated yield grade (CYG) was generated using the USDA Yield Grade equation (Busby and Loy, 2000), based on each animal's reported HCW, backfat thickness over the 12th rib, KPH, and LM area. Individual final shrunk live pay weight was provided in the data set from the feedlot and used to calculate ADG over the feeding period. Arrival weights were utilized to place each animal into a categorical arrival weight variable. The variable was based on U.S. feeder cattle weight price ranges consisting of: 136 to 180 kg (3WT), 181 to 226 kg (4WT), 227 to 272 kg (5WT), 273 to 318 kg (6WT), 319 to 363 kg (7WT), 364 to 408 kg (8WT), and greater than 409 kg (9WT).

Two categorical variables were created to represent the amount of time between initial BRD treatment and either arrival or harvest. The first variable used weeks on feed from arrival to initial BRD treatment to place each animal in categorical time variable (WKFA), which consisted of 14 categories (wk 1 through 14 post-arrival). The second variable measured weeks on feed from initial treatment for BRD to harvest (WKTH), and was broken into 44 weekly categorical variables (wk 1 through 44 from treatment to harvest). Descriptive statistics of the data were then generated using JMP (JMP Version 5.1, SAS Inst. Inc., Cary, NA).

An economic model was created to incorporate performance and health into a single figure allowing comparisons between cattle using similar methodology to previous studies of feedlot health (Gardner et al., 1998; White et al., 2007). The model calculated individual animal net returns minimizing economic variation due to seasonal or long-term market conditions and reflecting differences related to cattle performance. Net return for each animal was calculated (Equation 1) using the animal's individual gender, arrival weight class, days on feed (arrival to harvest), number of treatments, ADG, and carcass characteristics.

(1) Net Return = Base Price – Grid Price – Total Expenditures – Feeder Price

Base price was the average USDA boxed beef cutout value from November 1996 through April 2005 (Livestock Marketing Information Center, 2008a). The grid price was the average USDA monthly cattle premiums and discounts for slaughter steers and heifers over the same time period (Livestock Marketing Information Center, 2008b). Total expenditures represent the sum of health, processing, yardage, and feed costs. Treatment costs were fixed at $11.09/treatment (National Animal Health Monitoring System, 2000), processing at

$20.00/animal, yardage $0.20/animal per day, and feed costs at $0.88/kg of gain. Feeder price was the average USDA Oklahoma City monthly feeder calf price aggregated by weight class from January 1996 through February 2005 (Livestock Marketing Information Center, 2008c). Using the entrance and harvest price averages over this time period allowed us to account for feeder and fed price variability associated with multiple stages of the cattle cycle.

Statistical analysis

Before dead cattle were removed from the dataset, logistic regression models using the GLIMMIX procedure of SAS (Version 9.1, SAS Inst. Inc., Cary, NC) were used to determine if case fatality risks were ($P < 0.05$) different between WKFA categories for each BW class. As the data consisted entirely of cattle treated for BRD, case fatality risks were considered as any mortality after initial treatment divided by total number of initial treatments for each weekly category. For each arrival BW class, models included the proportion of treated cattle that died (case fatality) for each weekly category as the dependent variable, WKFA as the independent variable, and a random effect to account for lack of independence among cattle within the same pen. Case-fatality risks were not assessed for WKTH because there were no slaughter dates for mortalities. Thus, no WKTH category could be assigned.

To assess the factors associated with differences in estimated net returns, generalized linear mixed models at the individual animal level were developed using the GLIMMIX procedure in SAS (Version 9.1, SAS Inst. Inc., Cary, NC). A random effect for pen was used in all models to account for the lack of independence among individual animals within the same pen. Month, year, and the interaction between month and year were also included as random effects. Model-adjusted means were used to compare levels of effects that were significant at the $P < 0.05$ level. The first analysis investigated differences in net returns based on fixed effects representing gender, WKFA, risk code, arrival weight class, and the interaction between WKFA and all other fixed effects. We determined a priori that our objective was to assess effects related to the timing of initial treatment for BRD, and based on standard model building strategies for observational data we created two-way interactions only involving the exposure variable of interest (Dohoo et al., 2003). Therefore, two-way interactions between WKFA and all other fixed effects were investigated. The results from this initial model indicated a significant ($P < 0.05$) interaction between WKFA and weight class.

The same analysis described above was performed using the WKTH variable instead of WKFA. Results from the initial WKTH model indicated an interaction between WKTH and BW class ($P < 0.05$). However, due to sparse data in certain weeks for some BW classes, the model-adjusted mean values for the interaction between these effects could not be estimated. Therefore, we partitioned the data set by BW class strata (Jewell, 2004) and utilized 7 models, 1 for each BW class, for both WKFA and WKTH to assess the effects of disease timing separately within each BW class.

In order to further investigate observed differences in estimated net returns, we assessed ADG, CYG, HCW, days on feed, and number of times treated across both WKFA and WKTH categories using the same models as for net return values. In brief, generalized linear mixed models were used, to model each arrival BW class with random effects for pen, month, year, and the interaction between month and year. Potential differences in the respective performance or health variables were based on individual animal gender, WKFA or WKTH, risk code, and arrival BW class. Therefore, each performance model was estimated once with WKFA as an explanatory variable and once with WKTH as an explanatory variable. In addition, the proportions of cattle grading USDA Choice or above for each respective week category were analyzed with logistic regression models using the GLIMMIX procedure in SAS. The probability of grading Choice or above for each animal within each week category was modeled as the dependent variable and either WKFA or WKTH was the independent variable. These models included a random effect to account for lack of independence among cattle within the same pen.

Results

The number of cattle treated within each BW class are displayed in Table 2.1; descriptive statistics for performance measures, carcass traits, and each BW class are presented in Table 2.2. Days on feed at first treatment averaged 30 d, and the population distribution is plotted by WKFA in Figure 2.1. Days on feed from treatment to harvest averaged 161 d with 71.9% of cattle treated between wk 31 and 16 from harvest (Figure 2.2). The quality grades of the 31,131 cattle were: 59% select, 35% choice, 4.9% standard, 0.2% prime, and 0.2% other (hard bone, dark cutter). The overall morbidity and mortality in the feedlot during the study period was 17.3% and 0.80% respectively. Of the cattle in this study, 1,332 died; resulting in an overall case

fatality risk of 4.27%. Case fatality risk was associated ($P < 0.05$) with WKFA for all BW classes, but displayed no apparent ascending or descending pattern across the weekly categories.

Effects of time from arrival to treatment (WKFA) on estimated net returns

The initial analysis of estimated net returns indicated that gender, risk code, BW class, and the interaction of BW class and WKFA were all significant (Table 2.3). For the estimated net returns BW class-specific models, the 3WT cattle displayed a main effect ($P < 0.05$) of gender, whereas the 4WT, 5WT, and 6WT models indicated both gender and WKFA as main effects ($P < 0.05$). For the 7WT cattle, gender, risk code, and WKFA were all associated with net returns ($P < 0.05$), yet for 8WT cattle only WKFA was associated with net returns ($P < 0.05$). Only risk code ($P < 0.05$) was associated with estimated net returns for the 9WT cattle.

Our primary interest in assessing differences in estimated net returns was the measure of time relative to arrival (WKFA). Of the 7 BW classes examined, 5 (4WT, 5WT, 6WT, 7WT, and 8WT) displayed a WKFA effect ($P < 0.05$). The 4WT cattle had very few differences between WKFA categories, yet wk 1 and 2 were lower ($P < 0.05$) than wk 5, 7, 10, and 13 (Figure 2.3). The 5WT and 6WT cattle exhibited lower estimated net returns ($P < 0.05$) during wk 1 compared to any of the following wk during the first 5 wk on feed (Figure 2.3). Estimated net returns for the 6WT cattle were ($P < 0.05$) lower late in the feeding phase (wk 12 and 14) as compared to early in the feeding phase (wk 2, 3, 4, and 5) (Figure 2.3). The other BW classes (7WT and 8WT) displayed the lowest net return figures late in the feeding phase with no differences in earlier weeks. The 7WT cattle had lower estimated net returns ($P < 0.05$) during wk 14 compared to all previous weeks with the exception of 11, 12, and 13 (Figure 2.3). The 8WT cattle had lower estimated net returns ($P < 0.05$) wk 12, 13, and 14 as compared to any proceeding weeks during the feeding phase (Figure 2.3).

Effects associated with individual performance and health outcomes (WKFA)

For the models of ADG, the 3WT cattle displayed differences ($P < 0.05$) associated with gender, whereas the 4WT cattle displayed differences ($P < 0.05$) associated with gender and risk code. The 5WT, 6WT, 7WT, and 8WT cattle had differences ($P < 0.01$) based on gender, risk code, and WKFA. The 9WT cattle had differences ($P < 0.05$) in ADG due to WKFA. For all CYG models, there was no effect of WKFA ($P > 0.05$), but several other effects were significant at $P < 0.05$. For the 3WT and 5WT cattle, gender was an important effect ($P < 0.05$), whereas

gender and risk code were important effects in the 4WT and 6WT models ($P > 0.05$). For the 7WT cattle only risk code was the only effect associated with CYG ($P < 0.05$). The 8WT and 9WT had no effects associated with CYG ($P > 0.05$). For the HCW models, the 3WT, 4WT, and 9WT analyses showed difference associated with gender ($P < 0.01$). The model for 5WT, 6WT, 7WT, and 8WT cattle exhibited effects ($P < 0.05$) of gender and risk code. With days on feed as the dependent variable, risk code was significant ($P < 0.05$) for the 3WT cattle. The 4WT, 7WT, and 8WT cattle had effects ($P < 0.05$) of gender and risk code. Both 5WT and 6WT analysis indicated effects ($P < 0.05$) of gender, risk code, and WKFA. Finally, the 9WT analysis of days on feed exhibited an effect ($P < 0.05$) of gender. Number of times treated was considered a health outcome for each animal and differed by WKFA ($P < 0.05$) for all BW classes except 9WT. The times treated for 5WT cattle also had an effect ($P < 0.01$) of gender. The final performance outcome analyzed was the probability of grading Choice or above within each week category. For all BW classes, there were no differences ($P > 0.05$) between the probability of an animal grading Choice between WKFA weeks.

The effect of WKFA on performance and health outcomes that could be contributing to differences in estimated net returns was our primary interest. The 4WT cattle had a greater ($P < 0.05$) number of treatments when initially treated early in the feeding phase (wk 1 and 2) compared to cattle treated later in the feeding phase (Figure 2.4). For the 5WT cattle, ADG was higher ($P < 0.05$) wk 1 as compared to any subsequent week with the exception of wk 3, 9, 11, and 14. Hot carcass weight was greater ($P < 0.05$) for 5WT cattle treated wk 9, compared to other weeks with the exception of 10 and 11 (Figure 2.5). Days on feed were greater ($P < 0.05$) for cattle treated wk 2 and 9 compared to other weeks with the exception of wk 7, 10, 11, 12, and 13. In addition, number of times treated was greater ($P < 0.05$) early in the feeding phase (wk 1 to 3) compared to subsequent weeks (Figure 2.4).

The 6WT cattle had increased ADG ($P < 0.05$) if treated wk 1 compared to all subsequent weeks except wk 4 and 13. Cattle treated wk 14 displayed lower HCW as compared to earlier weeks with the exception of wk 12 (Figure 2.5). These cattle also had a decrease ($P < 0.05$) in days on feed if treated wk 14, compared to others except wk 7, 9, 11, and 12. Finally, the number of times treated was different ($P < 0.05$) between the first 3 wk of the feeding phase (higher early and then decreasing), and the treatments for the first 3 wk were all greater ($P < 0.05$) than any subsequent weeks (Figure 2.4).

40

For the 7WT cattle, ADG was greater ($P < 0.05$) for cattle treated wk 1, with the exception of wk 8 and 13. These cattle also had lower ($P < 0.05$) HCW when treated late in the feeding phase (wk 11 and 14) (Figure 2.5). The 7WT cattle also were treated more times ($P < 0.05$) wk 2 as compared to all other weeks, with the exception of wk 3, 13, and 14 (Figure 2.4).

The 8WT cattle were the final group in which WKFA was associated ($P < 0.05$) with estimated net returns. There was an effect ($P < 0.05$) of WKFA on ADG, but there was no apparent ascending or descending pattern across weeks (data not shown). The 8WT cattle had lower ($P < 0.05$) HCW if treated late in the feeding phase (wk 12 and 13) compared to other weeks, with the exception of wk 8, 9, and 14 (Figure 2.5). The number of times treated also was associated ($P < 0.05$) with WKFA. Cattle that were treated wk 13 had more treatments than those treated other weeks except wk 1, 12, and 14 (Figure 2.4).

Effects of weeks from treatment to harvest (WKTH) on estimated net returns

In the initial analysis assessing effects on net returns related to weeks from treatment to harvest, gender, WKTH, BW class, the interaction between BW class and WKTH, gender and WKTH were all significant (Table 4). Data were then stratified and effects within BW classes assessed individually. The 3WT and 9WT cattle displayed a main effect ($P < 0.05$) of gender whereas the 4WT and 7WT analyses exhibited effects ($P < 0.05$) of gender and WKTH. The 5WT, 6WT, and 8WT cattle all displayed effects ($P < 0.05$) of gender, risk code, and WKTH. All weight classes that had a WKTH effect ($P < 0.05$) and displayed a descending pattern in estimated net returns (Figure 2.6). When examining the 4WT cattle there were several WKTH (wk 1, 2, 3, 5, 6, 7, 43, and 44) in which no cattle were treated for BRD. Results indicated that cattle treated for respiratory disease wk 39 displayed greater estimated net returns ($P < 0.05$) compared to cattle that were treated wk 11 (Figure 2.6). Cattle in the 5WT class treated for respiratory disease during weeks further from harvest also demonstrated greater estimated net returns (wk 44 to 42) compared to wk 5 (Figure 2.6). The 6WT cattle treated during wk 43 exhibited greater estimated net returns ($P < 0.05$) in comparison to cattle treated wk 12 to 4 (Figure 2.6). For 7WT cattle, there were weeks far from harvest (wk 44, 42, 41, and 40) in which no treatments occurred, but data still indicated a very similar pattern in net returns to the 6WT cattle, with greater estimated net returns ($P < 0.05$) during wk 32 to 24 compared to wk 4 to 1 from harvest (Figure 2.6). The final BW class that displayed a significant WKTH effect was

the 8WT cattle, and these had several weeks that were not able to be assessed due to the fact that no cattle were treated for respiratory disease during wk 44 to 36 and 34 to 33. However, estimated net returns for the 8WT cattle still display a similar pattern as the BW classes previously discussed as wk 25, 24, 23, 21, and 20 were all greater ($P < 0.05$) than wk 4 and 1 (Figure 2.6).

Effects associated with individual performance and health outcomes (WKTH)

Analyses on performance and health outcomes by each arrival BW category indicate several notable findings. When ADG was the dependent variable, the 3WT cattle displayed effects ($P < 0.01$) of gender and WKTH. For the 4WT, 5WT, 6WT, 7WT, and 8WT cattle, effects ($P < 0.05$) included gender, risk code, and WKTH. The 9WT cattle had no important effects ($P > 0.05$).

With CYG as the dependent variable, gender had an effect ($P < 0.01$) on the 3WT cattle. The gender effect plus WKTH were associated ($P < 0.01$) with CYG for 4WT cattle. Gender, risk code, and WKTH were all associated ($P < 0.05$) with CYG for 5WT cattle. For the 6WT and 7WT cattle risk code and WKTH were both important effects ($P < 0.05$). The 8WT cattle had WKTH as an effect ($P < 0.05$), and the 9WT had no important effects ($P > 0.05$).

For the HCW outcome, the 3WT, 4WT, and 9WT cattle were affected ($P < 0.01$) by gender and WKTH. The 5WT, 6WT, and 7WT had those effects plus risk code ($P < 0.01$). When days on feed was the dependent variable, the 3WT and 5WT cattle had effects ($P < 0.05$) of risk code and WKTH. Weeks on feed from treatment to harvest (WKTH) was associated ($P < 0.05$) with HCW for the 4WT and 9WT cattle. Finally, the 6WT, 7WT, and 8WT cattle had effects ($P < 0.05$) of gender, risk code, and WKTH. With number of times treated as a health outcome, the 3WT and 9WT cattle had no associated effects ($P > 0.05$). The 4WT, 5WT, 6WT, 7WT, and 8WT cattle all had WKTH as an effect ($P < 0.05$). Analysis of Choice or above grading within each weeks category could not be performed using WKTH as the independent variable, as data were too sparse among many week categories. Therefore, differences in carcass performance across weeks on feed from treatment to harvest were not evaluated.

The effect of time from treatment to harvest (WKTH) was our primary interest for assessing differences in performance and health outcomes that could be contributing to differences in estimated net return. Models with ADG, CYG, HCW, days on feed, and number

of times treated as dependent variables all had associations ($P < 0.05$) with WKTH. The 4WT to 8WT cattle all displayed an ascending pattern in ADG between WKTH categories with differences ($P < 0.05$) among weeks throughout the feeding phase (going from treatment to harvest). For the performance models with CYG as the dependent variable there was no apparent pattern between WKTH categories, although there are some differences ($P < 0.05$) among weeks for the, 4WT, 5WT, 6WT, 7WT, and 8WT cattle. In contrast to the ADG models, HCW were descending across WKTH categories (going from treatment to harvest) for 4WT, 5WT, 6WT, 7WT, and 8WT cattle. Days on feed from entry to harvest also displayed a descending pattern across WKTH categories, with differences ($P < 0.05$) among weeks throughout the feeding phase for the 4WT, 5WT, 6WT, 7WT, and 8WT cattle. Since the pattern of relationships between performance measures and WKTH were similar across all BW categories we used results from the 5WT analysis for illustrative purposes (Figure 2.7).

Discussion

Our research provides unique information on performance and health outcomes associated with the timing of BRD treatment during the feeding phase. Other research evaluating the impact of BRD on performance and health factors has focused on comparing healthy and sick cattle over the entire feeding phase (Gardner et al., 1999; Roeber et al., 2001). We found that performance and health measures differ based on when cattle are first treated from BRD relative to arrival and harvest, and these associations depend on the arrival weight class. Our conclusions are based on retrospective individual animal data from over 5 yr that include multiple measures of performance and health, and analyses that use estimated individual animal net returns as a standardized screening metric to identify potential biological differences.

The temporal distribution of initial BRD treatments in our dataset was similar to findings from other research. Thompson et al. (2006) found 87% of first treatments occurred within first 35 d and Faber et al. (1999) described 81% of first treatments within the first 42 d. Martin and Meek (1986), indicated that BRD cases peaked between d 7 and 14 on feed and then declined. In our data, 74% of cases occurred in the first 42 d and BRD cases peaked during wk 2 post-arrival and then declined (Figure 2.1). When examining data from treatment to harvest (WKTH), the cases appear to be normally distributed (Figure 2.2). This is not surprising given that our data set included cattle from a wide range of initial weights resulting in variation in the total days on

43

feed. Therefore, although most cattle were treated relatively close to arrival (WKFA) the number of weeks between treatment and harvest (WKTH) varied greatly based on initial weight of cattle. Evaluations of the amount of time between treatments until harvest have not been described in the literature. The feedlot that provided our data does not harvest all cattle from the same arrival lot on the same date, but rather harvests subsets of the cattle as they finish. Data for our study represent only cattle identified and treated for BRD within the first 100 d of arrival in a single commercial feedlot. Results should be applied carefully as factors influencing the outcomes may vary by feedlot. Also, our data were analyzed as a cross-sectional observational study and thus no direct causal inferences can be drawn. Further research utilizing data from multiple different feedlots and evaluating cattle treated at different times and with different treatment protocols would provide additional insight into the effect of disease timing on health and performance.

We included placement month and year to adjust for variation in seasonal and management changes over the time period in the standardized economic model. Previous literature illustrates that cattle sex, season, and year impacts cattle performance and should be accounted for in an analysis of this nature (Schake, 1996). Cattle that died after treatment did not have performance records, and the economic loss from death causes high variability in net returns. Therefore, we removed dead cattle and just compared data on harvested cattle, which allowed us to efficiently address our objectives, but does not allow us to assess the economic impact of mortality. We did assess the case fatality risks for studied cattle and found few differences between WKFA categories. However, visual evaluation of the data did not reveal a consistent ascending or descending pattern to the case fatality rate between WKFA categories; therefore, we believe our findings are still indicative of the population as a whole. We were unable to evaluate case fatality risks by WKTH as cattle that died did not have the harvest date necessary to assign a WKTH category.

Assessment of effects of weeks from arrival to treatment (WKFA)

The analysis evaluating the timing of BRD treatment after arrival illustrated an interaction between WKFA and arrival BW class. Although WKFA was associated with net returns for the 4WT cattle, there were few major differences among weeks. For the 5WT cattle, net returns in wk 1 were lower than any other week within the first 5 wk on feed.   When

comparing common performance measures (e.g. ADG, HCW) there were very few differences between WKFA categories for 5WT cattle, and none that would explain the difference in estimated net returns. The fact that we found few significant differences in ADG in this BW category might be explained by the length of recovery time cattle had from disease identification to harvest. Earlier work by Thompson et al. (2006), found that BRD treatment status impacted ADG early in the feeding phase (< d 35) more than it impacted overall ADG. Cattle entering the feedlot as 5WT had an average of 220 d from arrival to harvest and displayed very few significant ($P < 0.05$) differences in performance variables (ADG and HCW) across WKFA categories. Days on feed did not differ across WKFA categories, which illustrates that all cattle in this BW class had the same potential recovery time from BRD treatment to harvest.

A previous study by Faber et al. (1999) showed that the average number of times that steers with BRD were treated over the entire feeding phase was 1.7. In our data set, the average number of times treated over the feeding phase for both steers and heifers was similar at 1.6 times. However, in our study 5WT cattle treated for respiratory disease early in the feeding phase (wk 1, 2, and 3) were treated more times ($P < 0.05$) compared to those initially treated later weeks in the feeding phase (Figure 2.4). One potential explanation for the relationship is the number of days at risk for retreatment after the initial treatment of respiratory disease. Cattle identified and treated early in the feeding phase have more days at risk for further disease or treatment relative to cattle treated later in the feeding phase. This offers some explanation to the apparent negative association between the number of times treated and WKFA. Figure 2.4 illustrates that 5WT cattle treated for respiratory disease wk 1 were treated an average of 1.9 times over the feeding phase compared to cattle initially treated during wk 4, which were only treated 1.3 times on average. The difference in model estimated net returns between wk 1 and 4 was $7.54 (Figure 2.3). The economic difference attributable to the average times treated between wk 1 and 4 equates to approximately $6.65, which would account for the majority of the difference in estimated net returns among these weeks.

The 6WT cattle had lower estimated net returns early (wk 1) and late in the feeding phase (wk 14) (Figure 2.3). Performance measures again did not differ ($P < 0.05$) among weeks in the first 5 wk of the feeding phase. The lower estimated net returns for cattle in wk 1 could be explained again by a difference in the number of times treated as similar to the 5WT cattle. The 6WT cattle differed from the 5WT cattle in that they also experienced

45

decreased estimated net returns when treated late in the feeding phase. Cattle treated during wk 14 experienced lower HCW as compared to all other weeks with the exception of wk 12 (Figure 2.5). This difference in HCW was apparently driving the difference in estimated net returns for this week. Yield and quality grades were not different among the weeks; therefore, if we assume $2.58/kg of carcass weight (which is the average base price in the net returns model), then an average carcass from wk 4 would be worth $30.84 more than an animal treated wk 14. The difference in HCW would explain the disparity in estimated net returns between these weeks.

Heavier cattle (7WT and 8WT) displayed a different relationship between estimated net returns and WKFA than other BW classes as they only exhibited lower returns over the final few weeks of the evaluation period (Figure 2.3). There were few differences among number of times treated and ADG, with no differences between days on feed, or CYG with regard to the 7WT cattle. However, the 8WT cattle had differences in the number of times treated. The only factor that was lower ($P < 0.05$) during the final few WKFA categories for the 7WT cattle was HCW. Thompson et al. (2006) found that the greatest effect of respiratory disease on growth occurred during the early finishing period with little effect in the later period, but they were looking at all weight classes and not specifically 7WT and 8WT cattle, where recovery time to finish could be an issue. Research by Gardner et al. (1999) found that cattle that were treated for respiratory disease averaged HCW 7.5 kg less than cattle that were not treated. However, we found substantial variability in HCW among cattle treated in different weeks; up to a 12 kg difference was identified among weeks for all treated cattle, which suggests there may be substantial variability among sick cattle. For the 7WT cattle treated during wk 14, the model adjusted mean HCW of 338 kg was 12 kg lower than the wk 4 mean HCW of 350 kg (Figure 2.5). The cause for this variation is unknown but may be the result of different disease processes associated with days on feed at initial treatment or disease misclassification. Regardless, this finding indicates that the timing of initial treatment for BRD impacts HCW in 7WT cattle. There were no other carcass characteristics that differed. Therefore, with the base price of $2.58/kg, the HCW difference would equate to a $30.96 difference in carcass value, nearly accounting for the $37.56 difference exhibited in the estimated net return model. For the 8WT cattle, differences in estimated net returns between cattle treated late, as compared to earlier, may be attributed to both decreased HCW and an increase in the number of treatments.

Assessment of effects of weeks from treatment to harvest (WKTH)

An interaction ($P < 0.05$) between WKTH and arrival BW class was identified; likely related to the biological differences among cattle in different arrival BW. The lighter weight classes had fewer cattle treated close to harvest (e.g., 4WT wk 1 to 7) (Figure 2.6), as compared with heavier cattle which had very few cattle treated far from harvest (e.g., 7WT during wk 44 to 37) (Figure 2.6). Sparseness of data for these weeks likely caused the relationship between estimated net returns and WKTH category to differ by weight class. This effect was evident when we truncated the data set to only wk 10 to 35 (93% of the data) and the interaction of WKTH and BW class was no longer present (data not shown). For all 5 weight classes that exhibited a significant WKTH effect (Figure 2.6), there was a similar pattern of lower estimated net returns when cattle were harvested closer to their first BRD treatment date and greater net returns when harvested further from initial treatment.

Four performance factors were likely influencing differences in estimated net returns between WKTH weeks for all BW classes: times treated, HCW, days on feed from arrival to harvest, and ADG.   Hot carcass weight was lower when cattle were treated closer to harvest. The reduction in total BW gain (as judged by HCW) may be related to the decreased time between treatment and harvest that cattle have to regain weight lost after the disease event. Roeber et al. (2001) found that calves visiting the hospital 2 or more times had decreased HCW compared to healthy cattle ($P < 0.05$), and no statistical difference compared to cattle treated only once. Our data showed that differences in HCW among sick cattle were associated with how long the cattle were on feed from treatment to harvest.

Days on feed tended to be lower as cattle were treated closer to harvest. Inferences from this should be carefully interpreted as treatment date could influence the harvest date thereby modifying the days on feed. Cattle in this feedlot were harvested in subsets within pens based on estimated level of maturity and across all weight classes cattle treated late in the feeding phase were harvested sooner.

Average daily gain displayed an ascending pattern between WKTH categories as cattle were treated closer to harvest (Figure 2.7). This result is somewhat surprising as cattle treated closer to harvest displayed lower HCW. However, combining this with the fact that these cattle were on feed less days, the overall affect was an increase in ADG over the entire feeding period. As there were no differences in CYG among WKTH categories, it can be presumed that cattle

47

were harvested at a similar degree of physiologic maturity. Thus, cattle treated farther from harvest required more days on feed to finish; even though they finished with a heavier HCW, they were less efficient (in terms of ADG). Several authors (Wittum et al., 1996; Gardner et al., 1999; Thompson et al., 2006) have illustrated that a BRD event causes a depression in weight gain. Cattle treated early in the feeding phase (further from harvest) have more days for a decreased rate of gain causing them to require greater days on feed, yet lower ADG compared to cattle treated in close proximity to harvest. The number of times animals were treated displayed a descending pattern over WKTH categories. This finding could be attributed again to the days at risk for further treatment.

Conclusion

Evaluating differences in estimated net returns relative to treatment from arrival time (WKFA) and harvest (WKTH) illustrated a significant interaction with arrival weight class. When analyzing differences in performance and health outcomes, the only parameters that significantly differed between any of the weeks on feed categories were number of times treated (WKFA and WKTH), days on feed (WKTH only), ADG (WKTH only), and HCW (WKFA and WKTH). Both set of analyses indicated that the timing of initial BRD treatment is associated with health and performance outcomes.

In conclusion, we found that disease timing, when measured both relative to arrival and harvest, impacts performance and health outcomes. While our data were derived from a single feedlot we have demonstrated that the number of times cattle are treated and HCW appear associated with weeks from arrival to first treatment. Cattle treated further from harvest had higher estimated net returns related to an increased HCW that appeared to offset increased costs due to more treatments, longer days on feed, and decreased ADG. Further insight into the relationship between BRD timing and performance and health parameters could lead to management options that more effectively mitigate the economic impact of this extremely important disease syndrome in feedlot productions systems.

References

Busby, D., and D. Loy. 2000. Called versus calculated yield grades. ISU Beef Research Report. A.S. Leaflet R1730. Iowa State University, Ames, Iowa.

Dohoo, I., W. Martin, and H. Stryhm. 2003. Model-building strategies Veterinary epidemiologic research. Page 323 in Veterinary Epidemiologic Research. AVC Inc., Charlottetown, Prince Edward Island, Canada.

Edwards, A. 1996. Respiratory diseases of feedlot cattle in central USA. Bov. Pract. 30:5-7.

Faber, R., N. Hartwig, D. Busby, and R. BreDahl. The costs and predictive factors of bovine respiratory disease in standardized steer tests. 1999. ISU Beef Research Report. A.S. Leaflet R1648. Iowa State University, Ames, IA.

Gardner, B. A., H. G. Dolezal, L. K. Bryant, F. N. Owens, and R. A. Smith. 1999. Health of finishing steers: Effects on performance, carcass traits, and meat tenderness. J. Anim. Sci. 77:3168-3175.

Gardner, B. A., H. G. Dolezal, F. N. Owens, L. K. Bryant, J. L. Nelson, B. R. Schutte, and R. A. Smith. 1998. Impact of health on profitability of feedlot steers. OSU Animal Science Research Report. Oklahoma State University, Stillwater, OK.

Jewell, N. P. 2004. Interaction. Pages 148-164 in Statistics for Epidemiology. Chapman and Hall/CRC Press Co, New York, NY.

Livestock Marketing Information Center. 2008a. Weekly Beef Cutout Values. 2008. http://www.lmic.info/tac/spreadsheets/meat/wkcutval.xls Accessed January 10, 2008.

Livestock Marketing Information Center. 2008b. Weekly Carcass Price Premiums and Discounts. http://www.lmic.info/tac/spreadsheets/cattle/wkly (155) cattle premiums discounts.xls Accessed January 10, 2008.

Livestock Marketing Information Center. 2008c. Weekly and Monthly Oklahoma City Feeder Cattle Prices. http://www.lmic.info/tac/spreadsheets/cattle/okstrhfr.xls Accessed January 10, 2008.

Martin, S. W., K. G. Bateman, P. E. Shewen, S. Rosendal, and J. E. Bohac. 1989. The frequency, distribution and effects of antibodies, to seven putative respiratory pathogens, on respiratory disease and weight gain in feedlot calves in Ontario. Can. J. Vet. Res. 53:355-362.

Martin, S. W., and A. H. Meek. 1986. A path model of factors influencing morbidity and mortality in Ontario feedlot calves. Can. J. Vet. Res. 50: 15-22.

National Agricultural Statistics Service. 2006. Cattle death loss.
http://usda.mannlib.cornell.edu/usda/current/CattDeath/CattDeath-05-05-2006.pdf
Accessed March 3, 2008.

National Animal Health Monitoring System. 2000. Part III: Health management and biosecurity
in U.S. Feedlots, 1999. http://nahms.aphis. usda.gov/feedlot/ feedlot99/FD99pt3.pdf
Accessed January 10, 2008.

Roeber, D. L., N. C. Speer, J. G. Gentry, J. D. Tatum, C. D. Smith, J.C. Whittier, G. F. Jones, K.
E. Belk, and G. C. Smith. 2001. Feeder cattle health management: Effects on morbidity
rates, feedlot performance, carcass characteristics, and beef palatability. Prof. Anim. Sci.
17:39-44.

Schake, L. M. 1996. Performance of commercial feedlots, cattle, and employees, 1980-1994.
Prof. Anim. Sci. 12:151-161.

Smith, R. A. 1998. Impact of disease on feedlot performance: A review. J. Anim. Sci. 76:272-
274.

Thompson, P. N., A. Stone, and W. A. Schultheiss. 2006. Use of treatment records and lung
lesion scoring to estimate the effect of respiratory disease on growth during early and late
finishing periods in South African feedlot cattle. J. Anim. Sci. 84:488-498.

White, B. J., J. D. Anderson, W. B. McKinley, and J. Parish. 2007. Factor price disparity and
retained ownership of feeder cattle: An application of feedlot and carcass performance
data to farm-level decision making. J. Ag. App. Econ. 39:87-101.

Wittum, T. E., N. E. Woollen, L. J. Perino, and E. T. Littledike. 1996. Relationships among
treatment for respiratory tract disease, pulmonary lesions evident at slaughter, and rate of
weight gain in feedlot cattle. J. Am. Vet. Med. Assoc. 209:814-818.

Table 2.1 Number of cattle in each BW class first treated for respiratory disease within the first 100 d on feed (n = 31,131)

Weight class	Number of cattle	% of total cattle
3WT	840	2.71
4WT	4,781	15.36
5WT	10,966	35.23
6WT	9,021	28.98
7WT	4,074	13.09
8WT	1,171	3.76
9WT	278	0.89

Table 2.2 Mean and standard deviation for descriptive statistics of feedlot cattle treated for respiratory disease for the first time within the first 100 d on feed (n = 31,131)

Trait	3WT[1] Mean SD	4WT[2] Mean SD	5WT[3] Mean SD	6WT[4] Mean SD	7WT[5] Mean SD	8WT[6] Mean SD	9WT[7] Mean SD
Receive BW, kg	168.2 (10.9)	209.1 (12.4)	250.8 (12.8)	293.1 (12.9)	336.4 (12.6)	380.4 (12.2)	429.8 (20.4)
Ending BW, kg	470.8 (42.4)	491.5 (49.6)	513.4 (52.5)	538.0 (53.7)	557.1 (52)	572.8 (46.4)	598.0 (47.1)
ADG, kg/d	1.26 (0.19)	1.29 (0.21)	1.32 (0.22)	1.36 (0.24)	1.38 (0.27)	1.39 (0.30)	1.37 (0.37)
HCW, kg	299.6 (30.9)	313.4 (35.7)	327.7 (37.4)	344.3 (38.5)	356.3 (37.5)	366.2 (34.08)	380.8 (33.13)
Fat thickness, cm	1.10 (0.44)	1.12 (0.41)	1.10 (0.401)	1.10 (0.40)	1.08 (0.404)	1.09 (0.41)	1.06 (0.45)
LM Area (12th rib), cm^2	77.4 (10.1)	80.2 (10.5)	82.5 (10.8)	84.5 (10.9)	85.4 (10.7)	86.2 (10.7)	87.6 (11.2)
Calculated yield grade	2.76 (0.75)	2.75 (0.72)	2.74 (0.73)	2.77 (0.73)	2.81 (0.73)	2.86 (0.73)	2.89 (0.81)
KPH, %	0.0076 (0.013)	0.0038 (0.0102)	0.0026 (0.0087)	0.0028 (0.009)	0.0035 (0.0326)	0.009 (0.122)	0.034 (0.258)
Times Treated	1.57 (1.16)	1.67 (1.4)	1.64 (1.33)	1.57 (1.26)	1.50 (1.16)	1.44 (1.03)	1.46 (1.06)
Days on feed	241.5 (29.1)	221.0 (34.1)	200.6 (34.9)	182.5 (36.5)	161.1 (34.1)	140.6 (28.7)	125.4 (26.4)
Days on feed at first treatment (WKFA)	30.5 (24.2)	29.54 (24.9)	28.78 (24.7)	29.79 (24.7)	31.86 (24.9)	34.90 (24.6)	35.47 (26.5)
Days on feed from initial treatment date until harvest date (WKTH)	211 (37.1)	191.5 (43.1)	171.8 (43.8)	152.7 (46.2)	129.2 (44.6)	105.7 (39.9)	89.9 (39.4)
Net return ($)	11.77 (72.63)	3.11 (72.89)	2.51 (71.56)	9.82 (71.38)	10.10 (71.92)	9.24 (68.22)	0.94 (81.92)

[1]136 to 180 kg cattle

[2]181 to 226 kg cattle

[3]227 to 272 kg cattle

[4]273 to 318 kg cattle

[5]319 to 363 kg cattle

[6]364 to 408 kg cattle

[7]>409 kg cattle

Table 2.3 The F-value and P-value for the main effects and first-order interactions for the estimated net return models which included the measure of time from arrival to first treatment (WKFA) and the measure of time from first treatment to harvest (WKTH)

Effect (WKFA)	F Value	Pr > F
gender	524.65	<0.001
weight class	25.11	<0.001
risk code	4.29	<0.001
WKFA	0.95	0.498
weight class*WKFA	1.46	0.005
gender*WKFA	1.22	0.255
risk code*WKFA	1.02	0.429
Effect (WKTH)	F Value	Pr > F
gender	88.72	<.001
weight class	13.13	<.001
risk code	0.99	0.449
WKTH	4.09	<.001
weight class*WKTH	1.3	0.003
gender*WKTH	1.47	0.025
risk code*WKTH	0.95	0.711

Figure 2.1 Frequency distribution of cattle by weeks that they were initially treated for respiratory disease during the first 100 d after arrival to the studied feedlot
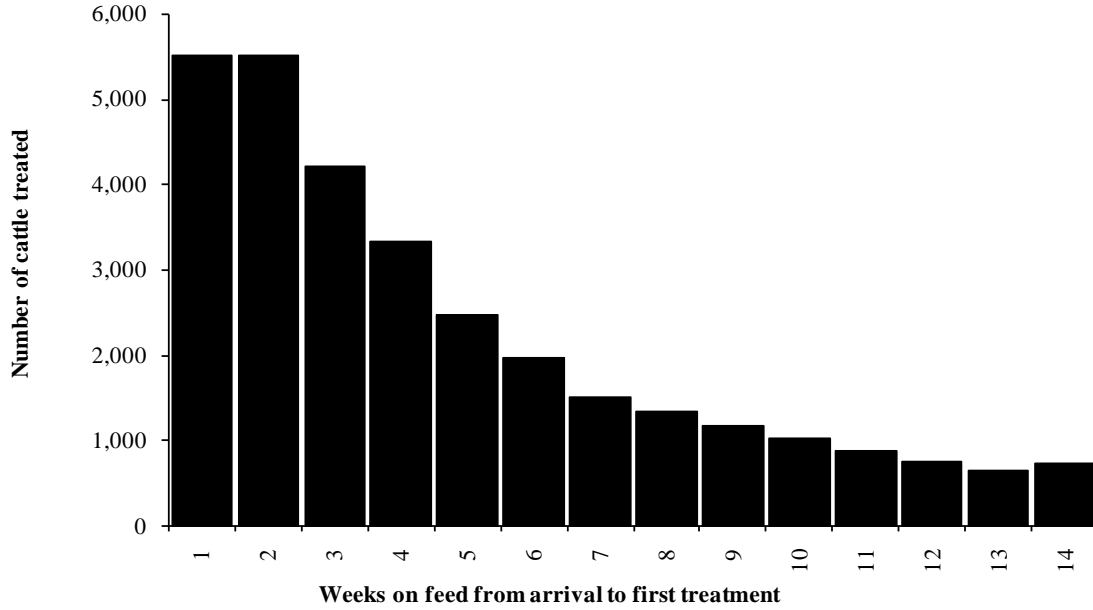
Figure 2.2 Frequency distribution of cattle initially treated for respiratory disease by weeks on feed from treatment to harvest
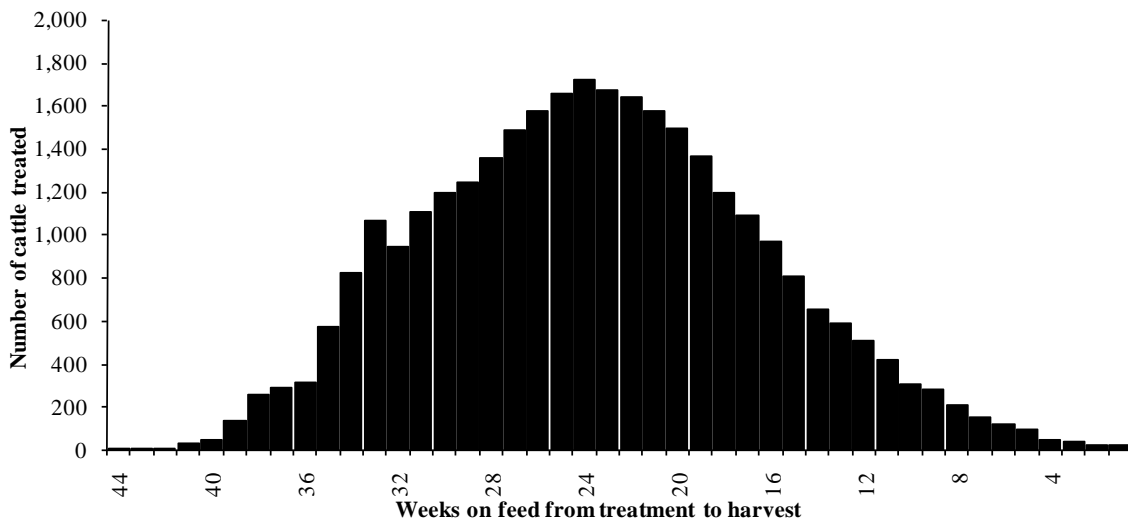
Figure 2.3 Model predicted net returns for all weights of cattle by weeks on feed from arrival to treatment for respiratory disease

[1]181 to 226 kg cattle

[2]227 to 272 kg cattle

[3]273 to 318 kg cattle

[4]319 to 363 kg cattle

[5]364 to 408 kg cattle

[6]Error bars represent SE of LS mean
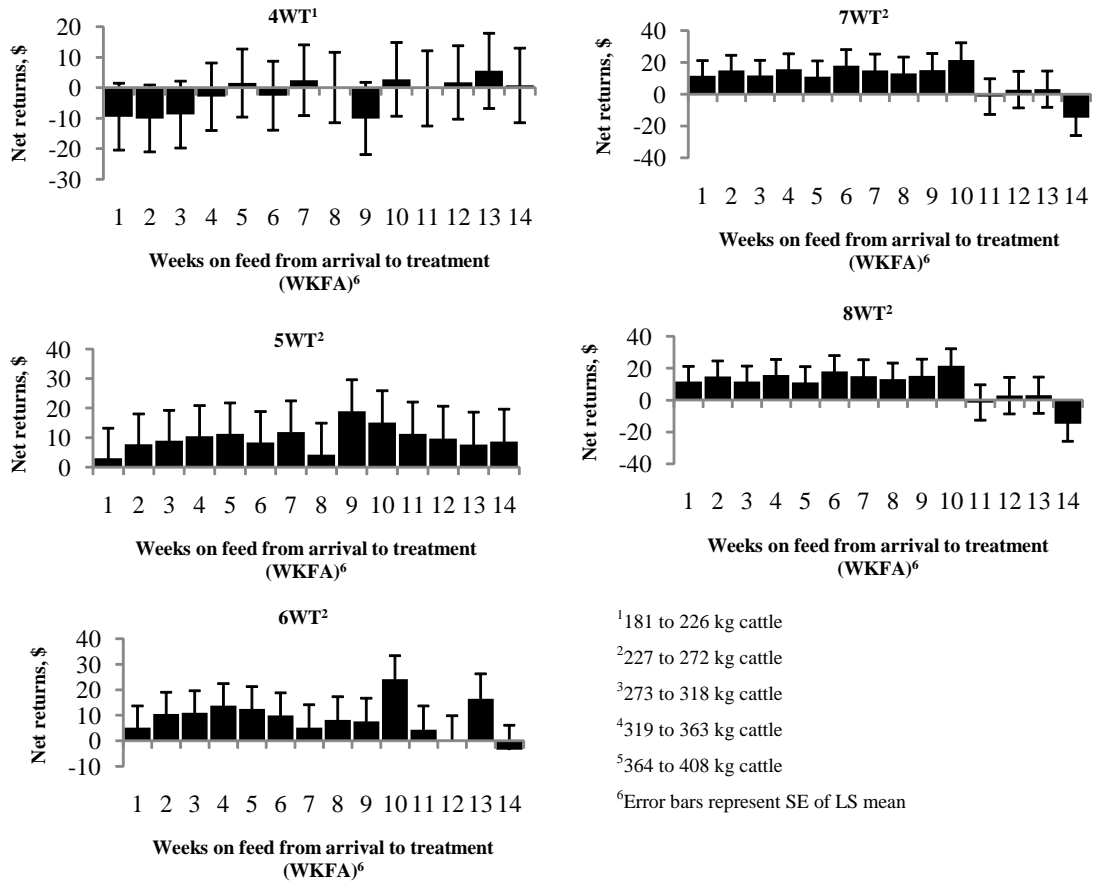
Figure 2.4 Model predicted number of times treated for all weight classes of cattle by weeks on feed from arrival to treatment

[1]181 to 226 kg cattle

[2]227 to 273 kg cattle

[3]273 to 318 kg cattle

[4]319 to 363 kg cattle

[5]364 to 408 kg cattle

[6]Error bar represent SE of LS mean
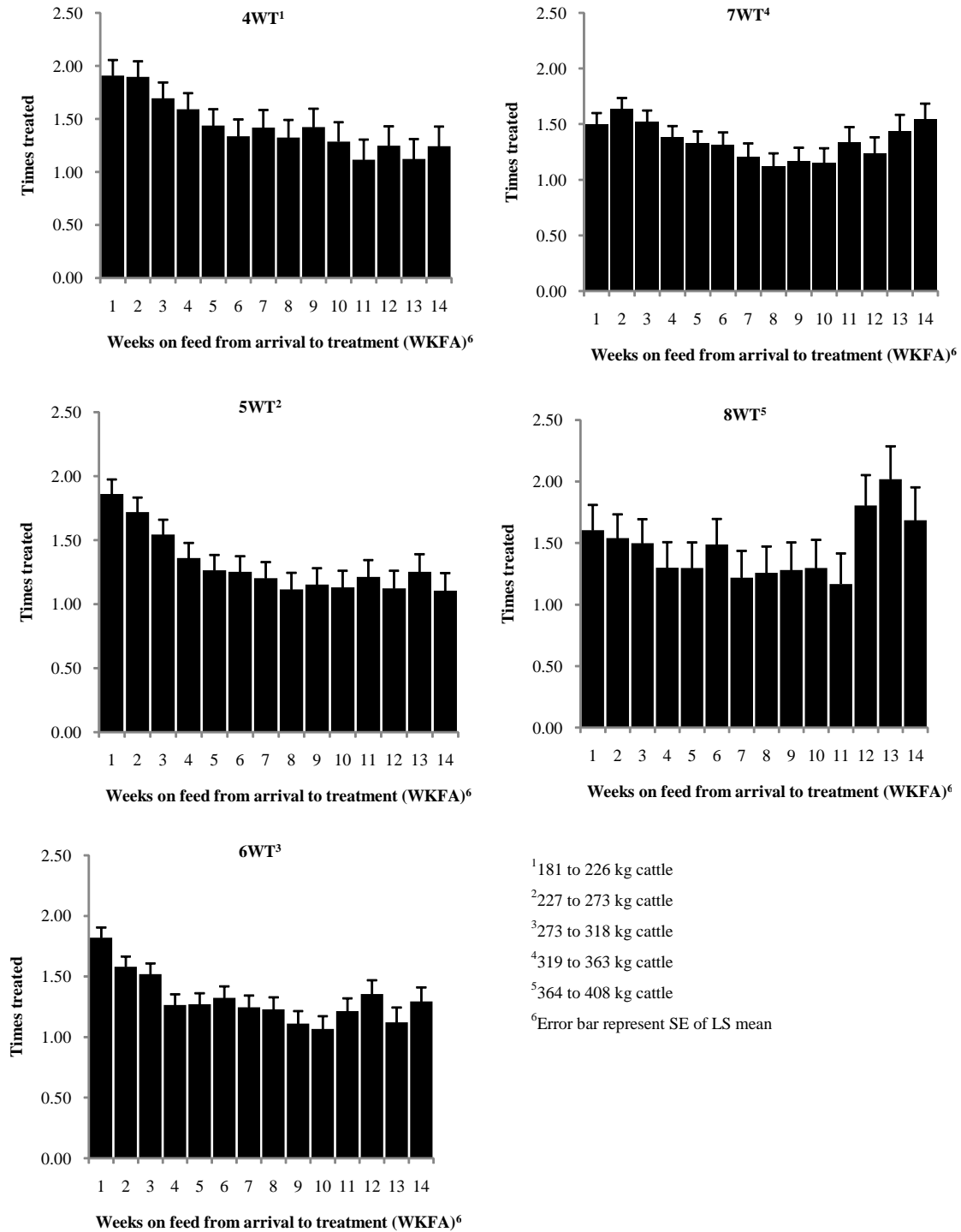
Figure 2.5 Model predicted HCW for all weight classes of cattle by weeks on feed from arrival to treatment

4WT[1]

5WT[2]

6WT[3]

7WT[4]

8WT[5]

[1]181 to 226 kg cattle

[2]227 to 273 kg cattle

[3]273 to 318 kg cattle

[4]319 to 363 kg cattle

[5]364 to 408 kg cattle

[6]Error bar represent SE of LS mean
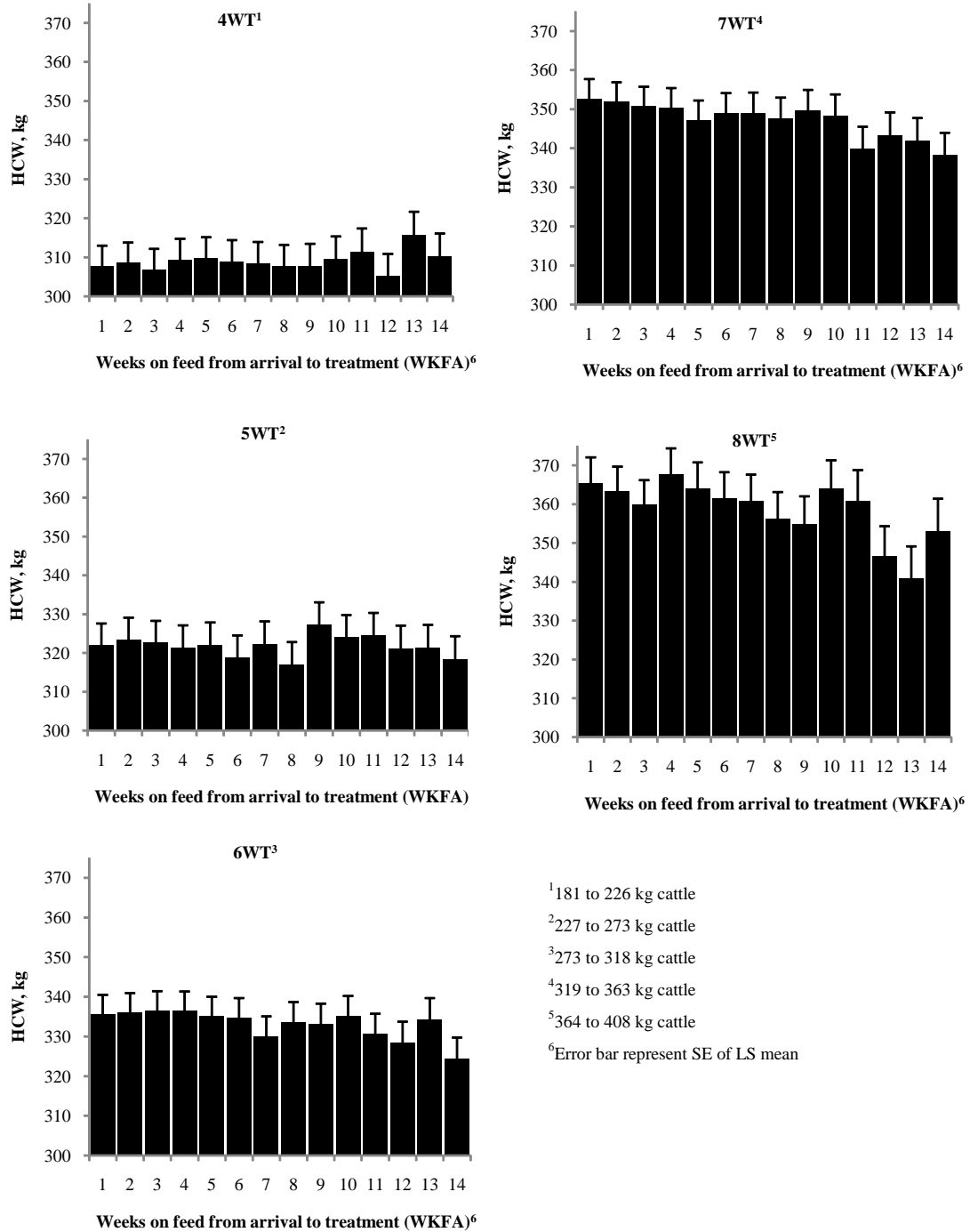
Figure 2.6 Model predicted net returns for all weights of cattle by weeks on feed from treatment to harvest

[1]181 to 226 kg cattle

[2]227 to 273 kg cattle

[3]273 to 318 kg cattle

[4]319 to 363 kg cattle

[5]364 to 408 kg cattle

[6]Error bar represent SE of LS mean

58
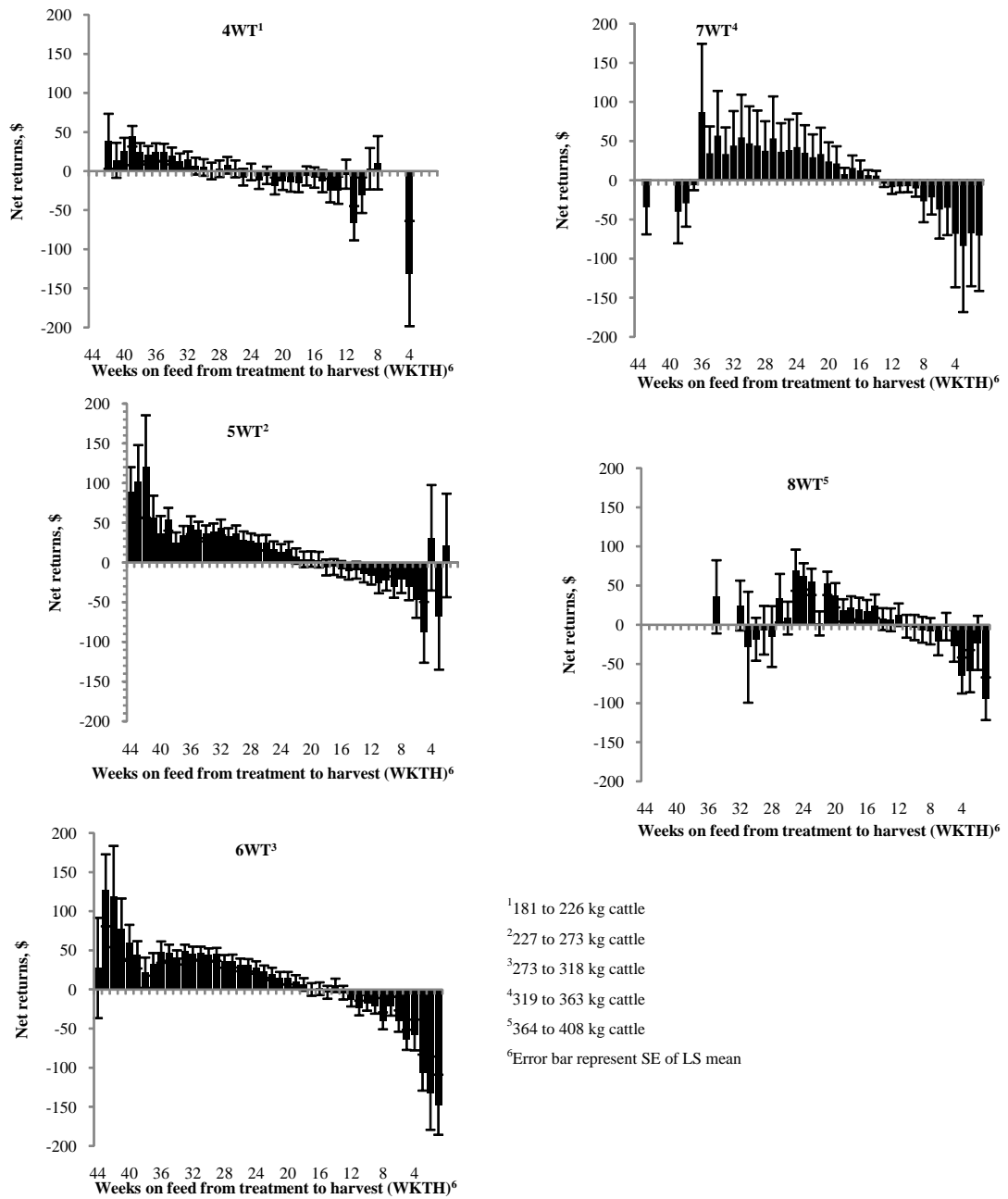
Figure 2.7 Model predicted estimates for performance and health measures (a. times treated, b. HCW, c. days on feed, and d. ADG) for 5WT cattle by the number of weeks on feed from treatment for respiratory disease until harvest
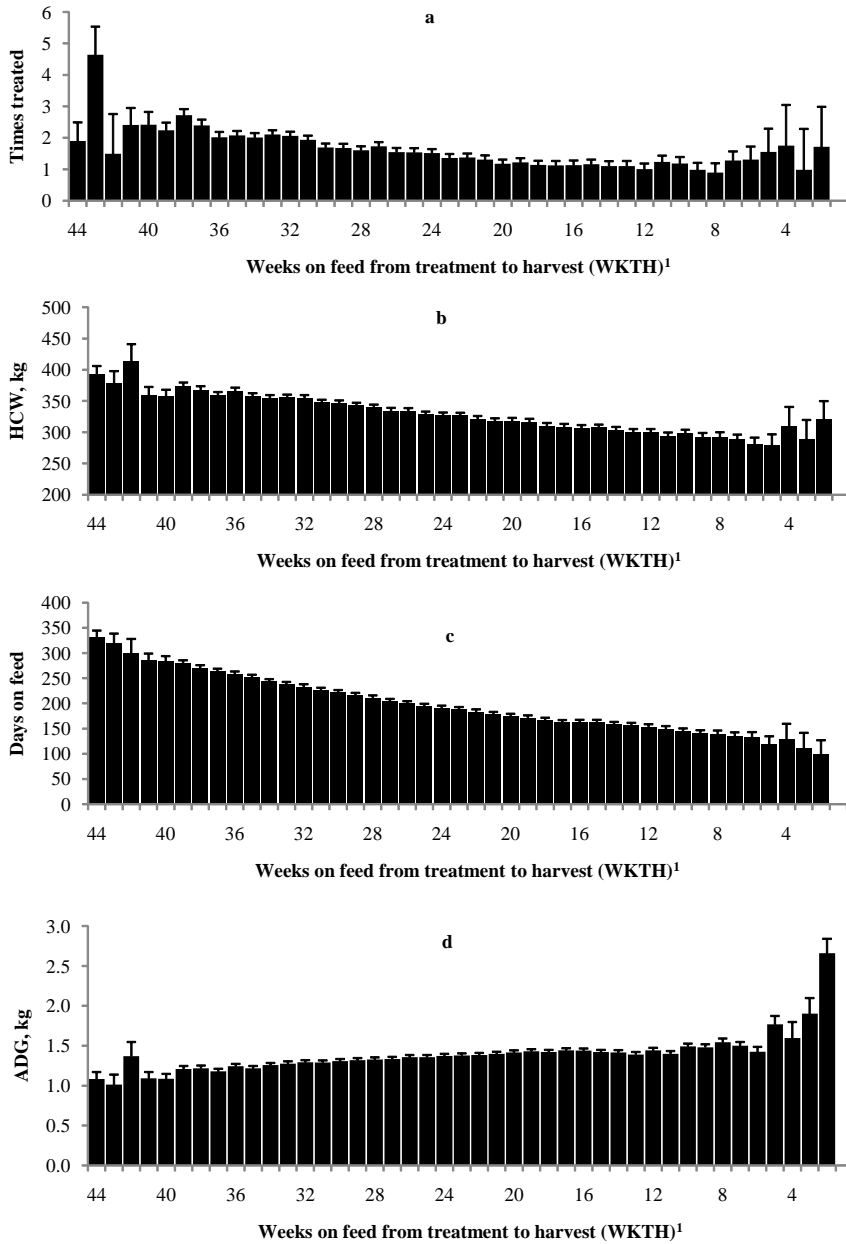
[1] Error bars represent SE of LS mean

CHAPTER 3 - Temporal distributions of respiratory disease events within cohorts of feedlot cattle and associations with health and performance indices

A.H. Babcock[a,b], D.G. Renter[a,*], B.J. White[b], S.R. Dubnicka[c], H.M. Scott[a]

[a]Department of Diagnostic Medicine and Pathobiology, College of Veterinary Medicine, Kansas State University, Manhattan, Kansas, United States

[b]Department of Clinical Sciences, College of Veterinary Medicine, Kansas State University, Manhattan, Kansas, United States

[c]Department of Statistics, College of Arts and Sciences, Kansas State University, Manhattan, Kansas, United States

Abstract

Bovine Respiratory Disease Complex (BRDC), the most common cause of post-weaning disease in North American beef cattle, is a multifaceted process involving pathogen, host, environment, and management factors. Although the importance of describing and evaluating the timing of BRDC cases has been recognized, a formal analysis of the temporal patterns of BRDC has not been described in the literature. Our objectives were to classify within-cohort temporal patterns of BRDC cases during the first 100 days at risk, using operational data from commercial feedlots, and then to evaluate associations among temporal patterns and common cohort-level measures of feedlot performance and health, while controlling for common potential confounders. We used retrospective cohort-level and individual animal health data (2000 – 2008) from 10 U.S. feedlots. We defined cumulative distributions representing the timing of cases within cohorts using the daily percentage of cases relative to the total number of cases within a cohort. Ward's hierarchical clustering method was used to group cohorts exhibiting similar cumulative distributions of BRDC cases. Linear mixed models and generalized estimating equations then were used to determine associations between temporal patterns and

economically important measures of cattle performance (mean daily weight gain, total days on feed, and carcass measures) and health (mortality risk and retreatment risk) outcomes, while accounting for possible confounding variables (gender, arrival month, arrival year, arrival weight, arrival risk classification, cumulative morbidity, and the feedlot itself). Cluster analysis identified seven different cohort-level temporal patterns of BRDC cases. Our independent variable of interest (temporal pattern) was associated with mean daily weight gain, total days on feed, and carcass weight, and the estimated effects were modified by arrival weight category and risk classification. Temporal patterns also were associated with USDA measures of carcass yield and quality that largely affect carcass price. We also found associations among temporal patterns and health outcomes (cumulative mortality and retreatment risk), and these effects were significantly modified by arrival weight and cumulative morbidity. Our results are the first to demonstrate that there are several temporal patterns of BRDC repeatedly observed among cohorts of feedlot cattle, and that these BRDC patterns may differentially affect cattle health and performance.

Keywords: Cattle; respiratory disease; temporal distribution; cluster analysis

Introduction

Bovine Respiratory Disease Complex (BRDC) has been the most common cause of post-weaning disease in North American beef cattle for decades (Vogel and Parrott, 1994; Edwards, 1996; Smith, 1998). Despite the development of vaccines, pharmaceuticals, and management systems designed to mitigate the effects of this syndrome, BRDC accounts for approximately 75% of feedlot morbidity and 50% of mortality (Edwards, 1996) and has been estimated to cost the U.S. beef industry approximately $750 million annually (Griffin, 1997). Incidence of BRDC within and among cattle populations is tremendously variable, resulting from the effects and interactions of multiple pathogen, host, environment, and management factors (Martin et al., 1982; Ribble et al., 1995; Griffin, 1998; Smith et al., 2001; Cusack et al., 2003). Cattle arrival weight, gender, phenotype and genotype, as well as factors related to season or weather, shipping distance, and previous nutrition and management are all widely accepted risk factors for BRDC (Martin et al., 1982; Ribble et al., 1995; Lechtenberg et al., 1998; Smith et al., 2001; Corbin and Griffin, 2006). Cumulative disease measures have provided good indications of the risk factors for, and impacts of BRDC in feedlots, yet the associations are based on the

magnitude of disease burden within a cohort while ignoring potentially important temporal patterns of BRDC occurrence (Sanderson et al., 2008).

Although published literature indicates that most BRDC cases in feedlot cattle occur within the first 45 days after arrival to the feedlot (Edwards, 1996), specific temporal patterns of BRDC cases within arrival cohorts have not been fully characterized for commercial feedlot cattle. Within-cohort temporal patterns may provide vital information regarding the identification and management of the syndrome (Booker et al., 2004), yet BRDC research and feedlot disease monitoring programs often focus on cumulative measures that represent the total number of disease events over the entire risk (feedlot) period for a cohort (lot or pen) of feedlot cattle, rather than when events occur. Previous research indicates that the timing of BRDC occurrence in individual feedlot cattle has important impacts on individual cattle health and performance (Thompson et al., 2006; Babcock et al., 2009). However, such individual animal-level data are not typically available in commercial feedlot production systems, which tend to monitor health and performance indices at the cohort (lot or pen)-level. Spatio-temporal dynamics of BRDC in European beef herds have been previously investigated, but the use clustering methods to group temporal distributions of BRDC within feedlot cohorts have yet to be described (Norstrom et al., 1999; Gay and Barnouin, 2009).

The objectives of our study were to classify within-cohort temporal patterns of BRDC cases during the first 100 days at risk, using operational data from commercial feedlots, and then to evaluate associations among temporal patterns and common cohort-level measures of feedlot performance and health, while controlling for common potential confounders.

Materials and methods

Data

We collected and verified individual health and cumulative cohort-level data that were recorded in 10 Midwestern U.S. feedlots during 2000 – 2008. Cohorts were defined by feedlots as "lots" of animals arriving to the feedlot that were purchased, assembled, managed and marketed similarly, but not necessarily housed together in the same physical location (pen) for the entire feeding period. These cohorts (lots) are the common aggregate unit in commercial feedlot production systems. For this study, we evaluated only those cohorts that had at least one

BRDC case, defined as an animal initially demonstrating clinical signs of BRDC (as determined by trained feedlot personnel) and treated with an antimicrobial.

Cluster analysis

Using a cohort-level aggregated data set, we created a new variable representing the daily count of new BRDC cases within the cohort over each of the first 100 days at the feedlot; the cumulative sum of which (for each cohort) represented the cumulative number of new cases for the first 100 days at risk. We then considered the cumulative distributions of the daily percentiles within a cohort during the study period. These distributions represented the timing of cases within cohorts, not the amount (magnitude) of cases, since for each cohort the final cumulative percentage of cases reached 100%. We then used a hierarchical clustering technique (Ward's method) to group cohorts with similar distributions of the daily percentage of cases (Ward, 1963). Ward's method is an agglomerative hierarchical clustering technique that has similarities to analysis of variance (ANOVA). Each cohort initially served as a cluster and clusters were merged using Ward's linkage function. This linkage function, specifying the distance between two clusters, was computed as the increase in the error sum of squares (ESS) each time two clusters are combined into a single cluster. Ward's method then chose the successive clustering steps so as to minimize the increase in ESS at each step (R version 9.2.1, R Development Core Team, Vienna Austria); the HCLUST function in R computed heights, a function of the ESS, at each step that two clusters were combined. We examined the heights for various numbers of clusters, and determined groupings of cohorts based on visual assessment of height values plotted against the number of clusters (R, 2010).

After the final clusters were defined, nonparametric smoothing methods (local-linear regression) were then used to obtain a curve and variability bands representing the temporal pattern for each identified cluster. Variability bands represent two standard errors from the estimate, similar to a 95 percent confidence interval. Hereafter, the term temporal pattern will be used to designate the smoothed curve representing a cluster of cohort distributions.

Risk factor analysis

Data management

To complete the second phase of our objectives, additional data were evaluated in comparison to the newly defined temporal patterns. Common cohort-level measures of cattle performance (mean daily weight gain, total days on feed, mean hot carcass weight, carcass quality, and carcass yield grade) and cattle health (cumulative mortality risk and cumulative retreatment risk) were the outcomes evaluated. Performance variables were calculated using only those animals that survived until harvest since the potential mortality effect was assessed in a separate analysis. Carcass quality and yield grades were based on the U.S. Department of Agriculture's system (USDA, 1997) and were reported by the abattoir as the number of animals within a cohort yielding each grade. Cumulative mortality risk was defined as death loss due to any cause for the entire time a cohort was in the feedlot, and cumulative retreatment risk represented risk of meeting the BRDC case definition more than once while in the feedlot.

Cohort-level covariates of interest included mean arrival weight, gender, month and year of feedlot arrival, cumulative BRDC morbidity risk, and respiratory risk code. For this analysis, only cattle cohorts arriving to feedlots from 2005 – 2007 in nine feedlots were used as other years and feedlots did not have complete data to assess the effects of the aforementioned covariates. Cohorts were also dropped from the analysis if they were classified as being of mixed gender or of Holstein breed due to sparse data in these categories. For carcass outcomes (weight, yield and quality grade), 106 cohorts could not be used in the analysis due to missing carcass data. Feedlots reported yield grade as the number of animals within a cohort that either graded Yield Grade One or Two and the number of animals that graded Yield Grade Four or Five. Similarly, for quality grade the feedlots reported the number of animals within a cohort that graded Choice or Prime. For our analysis, we only assessed one outcome variable representing yield grade (number of Yield Grade One or Two carcasses of total carcasses within the cohort) and one representing quality grade (number of Choice or Prime carcasses of total carcasses within the cohort), as these represent superior carcass yield and quality and are an economic incentive to the producers as they result in premiums added to the carcass sale price.

As others have done to account for trends over time (Scott et al., 2003), arrival year and month were combined into one serial variable, referred to as time, which ranged from 1 to 37. For this variable, 1 represented data from May 2005, 2 represented June 2005, and so on until 37 (representing May 2008). Risk code was a dichotomous variable; all feedlots had personnel who classified cohorts as "high" or "low" risk for respiratory disease following their standard

protocols which are based on visual appraisal of the cattle at arrival, cattle source, body size, transport time, and other factors. Common in commercial feedlots, this practice attempts to predict the cumulative BRDC burden for a group of cattle at arrival (Lechtenberg et al., 1998).

Descriptive statistics

Descriptive statistics were computed for data used in the analyses. For interval scale variables, minima, maxima, and quartiles were computed. Frequency tables were constructed for ordinal and nominal variables. These univariable statistics were also assessed after stratification by temporal pattern. The stratification allowed us to assess the distribution of risk factors across temporal patterns and determine potential confounders. Finally, frequency distributions were charted for all outcome variables.

Associations of temporal patterns with performance and health outcomes

Linear and logistic regression models were utilized to assess associations among outcomes of interest and the temporal BRDC patterns as defined by the cluster analysis, while controlling for potential confounders. All analyses were performed using Stata Version 10 (Stata Corp, College Station, TX, USA).

Mean daily weight gain per animal, total days on feed, and mean hot carcass weight per animal were all made available to us at the cohort level on a continuous scale; therefore, these were assessed with maximum likelihood estimated linear mixed models (XTMIXED), which included temporal BRDC patterns (covariate of interest), arrival weight, gender, time, cumulative morbidity, and risk code as covariates. Arrival weight and cumulative morbidity were both reported on a continuous scale, but did not meet linear assumptions in any of the bivariable analyses. Therefore, both were categorized based on biological and feedlot industry-relevant breaks. Arrival weight was categorized into seven categories (< 182kg, 182 - 271 kg, 272 - 317 kg, 318 - 362 kg, 363 - 408 kg, ≥409 kg). Total cumulative morbidity was categorized into four categories (0 to < 5%, 5 to < 10%, 10 to < 20%, and ≥ 20%). Time (month-year) was modeled as a categorical variable as defined above. Feedlot was included as a random effect (correlation structure specified as identity) to account for the lack of independence among cohorts within feedlots.

Significance testing for all stages of model building was assessed using a likelihood-ratio test comparing the full model to reduced model (Dohoo et al., 2003a). Main effect models were

fit utilizing manual backward selection (P < 0.05) starting with all covariates that were initially (P < 0.1) associated with the outcome in the bivariable model. If effects were deemed non-significant, but appeared to confound the relationship(s) between temporal pattern and the outcome being investigated, they were forced into subsequent models. Confounding was assessed during the bivariable stage of analysis by adding one covariate at a time to the bivariable model of the independent variable of interest (temporal pattern). If the coefficient for temporal pattern changed by >15%, confounding was assumed. Temporal pattern was allowed to remain in all models because it was the risk factor of interest (Dohoo et al., 2003c). Two-way interactions with temporal pattern (risk factor of interest) were fit subsequent to main effects models by screening the interactions individually while retaining all significant main effects. If interactions met the screening criteria of P < 0.1, they were included in the full model and backward selection was used to eliminate any sets of two-way interactions with P > 0.05. The manual screening procedure was used because our operating system would not support simultaneous evaluation of all two-way interactions for logistic models discussed below and for consistency we followed the same procedure for the linear models. Regression diagnostics for all final linear mixed models were performed by visually assessing standardized residuals plotted against the predicted values.

We used logistic regression models and generalized estimating equations (GEE) in Stata XTGEE to assess associations with performance (yield grade and quality grade) and health (mortality and retreatment) outcomes that were represented by a count in the aggregated data, but were ultimately measured on a binary scale at the animal-level. In addition to including the covariates listed above and a fixed effect for feedlot, the highest hierarchical variable (Dohoo et al., 2003b), we include cohort as a panel variable to account for correlation among binary observations within cohorts. Time was specified as the categorical variable described previously. The same model building strategies were used to construct the GEE models as were used for the linear mixed models. Independent correlation structure and robust standard errors were used in bivariable, main effect, and two-way interaction evaluations. For the final model, exchangeable correlation structure was specified to account for the lack of independence of animals within the same cohort. Since the likelihood ratio test is not valid for GEE models, Wald $\chi2$ tests were used to assess the overall significance of variables, or groups of indicator variables and interaction terms (all explanatory variables were categorical). Model diagnostics consisted of visually

assessing raw residuals plotted against predicted values, and assessments of quasi-likelihood (QIC) values were used to evaluate correlation structures (Hardin and Hilbe, 2003).

Results

Cluster analysis

Assessment of results from the cluster analysis of temporal distributions indicated that reducing the number of clusters resulted in relatively minimal, albeit slightly increasing, changes in values of height, as a function of ESS, until seven clusters were fit (Figure 1). However, reducing from seven to six clusters resulted in a relatively dramatic change, indicating two dissimilar clusters were combined (Ward, 1963). Thus, we determined that seven clusters provide the optimal grouping of temporal patterns within cohorts (Figure 1). Smoothed lines representing clusters of temporal patterns and their corresponding variability bands are displayed in Figure 2. Patterns One and Seven displayed the two extreme patterns in terms of timing of cases, where the majority of cases occurred either very early or very late in the study period, respectively. For Pattern One, approximately 80% of the BRDC cases occurred by day 10, whereas with Pattern Seven, the cumulative percentage of cases did not approach 80% until day 90. With some patterns, such as Temporal Patterns Two and Three, the majority of cases occurred later than Pattern One, but cases still accumulated relatively rapidly when they occurred; in contrast, for other Patterns (e.g., Five and Six) the percentage of cases increased more gradually over time. Of the 9,942 cohorts included in the cluster analysis, 1,639 (16%) fell in pattern One, 2,188 (22%) in Two, 1,874 (19%) in Three, 665 (7%) in Four, 1,789 (18%) in Five, 1,249 (13%) in Six, and 538 (5%) in Seven.

Descriptive statistics

Data for the risk factor analyses consisted of 7,553 cohorts representing a total of 1,226,806 feeder cattle. The 2,389 cohorts that were eliminated due to incomplete data were distributed across all seven temporal patterns (One = 18%; Two = 23%; Three = 18%; Four = 7%; Five = 17%; Six = 12%; Seven = 5%) proportional to the initial population described above. Of the analyzed cohorts, 73% were composed of males and 27% were composed of females. Cohort size on arrival to the feedlots ranged from 41 to 333 animals, with a median of 149 and a mean of 162 animals. Mean arrival weight of cohorts ranged from 110 to 480 kg, with a median

of 320 kg and mean of 315 kg. Cumulative within cohort BRDC morbidity for the first 100 days ranged from 0.3% to 84.3% with a 4.2% median and an 8.8% mean. Cumulative mortality ranged from 0% to 28.7% with a median of 1.3% and mean of 2.0%. Retreatment risk within cohorts ranged from 0% to 100% with a median of 17.2% and mean of 22.6%. Days in the feedlot ranged from 71 to 416 with a median of 178 and mean of 189 days. Mean daily weight gain per animal ranged from 0.5 to 2.1 kg with a median of 1.35 kg and mean of 1.35 kg. On average across all cohorts, 62.6% of animals were Yield Grade One or Two, and 42.9% of animals had Quality Grade of Choice or better. Mean hot carcass weight was 390 kg, with a 375 kg median. Risk code was "low" for 73% of the cohorts. The cohort-level frequency distribution of categories for each explanatory variable across the seven temporal patterns (described above) is displayed in Table 1.

Associations of temporal patterns with performance and health outcomes

Mean weight gain

Temporal pattern of BRDC morbidity was associated with mean daily weight gain in the bivariable analysis ($P < 0.01$). The coefficients representing the effects of Temporal Patterns Two and Three versus Pattern One were both negative and statistically significant (b= -0.04, 95% CI= -0.05, -0.03 and b= -0.02, 95% CI= -0.03,-0.01, respectively), while the coefficient for Temporal Pattern Seven (referent: Pattern One) was positive and statistically significant (b=0.04, 95% CI=0.02, 0.06). Gender, arrival weight, cumulative morbidity, risk code, and time were all determined to confound the relationship between temporal pattern and mean weight gain. In the main effects model, temporal pattern, gender, arrival weight, cumulative morbidity, risk code, and time were all significant.

The final model for mean daily weight gain included interaction terms for temporal pattern with each of arrival weight category and risk code (Table 2). Residual analysis indicated adequate model fit, and the random effect of feedlot accounted for 8.6 percent of the total variance. Generally speaking, as weight category decreased, mean daily weight gain across all temporal patterns decreased. Arrival weight appeared to modify the relationship between temporal pattern and mean daily weight gain largely in the lighter weight categories (i.e., 182 - 226 kg and < 182 kg). Risk code also modified the effect of temporal pattern on mean daily gain. In Pattern One, both high and low risk cohorts displayed similar mean daily weight gains.

However, with other temporal patterns this was not the case; mean weight gain was higher for low risk cohorts compared to high risk cohorts (Figure 3).

Days on feed

Temporal pattern was associated with days on feed in the bivariable analysis. Cohorts in Temporal Pattern Six and Seven required significantly fewer days on feed when compared to Temporal Pattern One (b = -9.1, 95% CI = -12.7, -5.4 and b = -19.9, 95% CI = -24.9, -14.9; respectively). Cohorts in Temporal Pattern Two were on feed significantly more days compared to Pattern One (b = 8.2, 95% CI = 5.1, 11.2). Gender, arrival weight, cumulative morbidity, risk code, and time were all determined to confound the relationship between temporal pattern and days on feed. Temporal pattern, gender, arrival weight, cumulative morbidity, risk code, and time were all significant in the main effects model.

In the final model, the relationship between temporal pattern and days on feed was modified by arrival weight and risk code (Table 3). The random effect of feedlot accounted for 5.1 percent of the total variance, and residual analysis indicated adequate model fit. The interaction between temporal pattern and arrival weight category indicated that all temporal patterns required increased days on feed as weight category decreased, but there were differences in days on feed within weight categories for the 182-226 kg and <182 kg cohorts (Figure 4). The magnitude of the difference of days on feed between low and high risk cohorts was fairly similar across all temporal patterns except for Pattern Seven, where the magnitude between the two appeared to be much smaller (Table 3).

Carcass weight

Bivariable analysis of mean carcass weight indicated a significant association with temporal pattern. All temporal patterns, with the exception of Pattern Seven resulted in significantly lighter carcasses at harvest when compared to Temporal Pattern One; coefficients ranged from -11.9 for Pattern Three (95% CI = -20.2, -3.6) to -19.4 for Pattern Two (95% CI= -27.3,-11.6). Gender, arrival weight, cumulative morbidity, and risk code were all determined to confound the relationship between temporal pattern and carcass weight. In the main effects model, temporal pattern, gender, arrival weight, cumulative morbidity, risk code, and time were all significant.

The effect of BRDC temporal pattern on carcass weight was significantly modified by arrival weight and risk code, as shown in Table 4. Residual analysis demonstrated adequate model fit, and the random effect of feedlot accounted for 5.2 percent of the total variance. Generally, carcass weights decreased as arrival weight category decreased, with a few exceptions (Figure 5). The magnitude of the modification of effect of temporal pattern by respiratory risk code was small.

Probability of Yield Grade One or Two carcasses

The bivariable model demonstrated that temporal pattern was associated with the probability of Yield Grade One and Two carcasses within cohorts. Temporal Patterns Three (OR=0.93, 95% CI=0.88, 0.98), Four (OR=0.93, 95% CI=0.87, 0.99), and Five (OR=0.92, 95% CI=0.87, 0.97) had lower odds of Yield Grade One and Two carcasses when compared to Pattern One. Arrival weight, gender, cumulative morbidity, risk code, and time were all determined to confound the relationship between temporal pattern and the probability of Yield Grade One and Two carcasses within cohorts. In the main effects model, temporal pattern, gender, weight category, and risk code were all significantly associated with the outcome.

In the final model, the effect of temporal pattern was modified by gender. Residual analysis demonstrated adequate model fit, and QIC indicated exchangeable correlation structure was appropriate for these data. In male cohorts, the percentage of Yield Grade One and Two carcasses generally decreased across Patterns One to Seven (Table 5).   However, this decreasing pattern was not apparent for female cohorts (Figure 6).

Probability of Choice or Prime carcasses

Temporal pattern was associated with the probability of a carcass grading Choice or Prime within a cohort in the bivariable analysis, with Pattern Three (OR=1.07, 95% CI=1.02-1.13), Six (OR=1.07, 95% CI=1.02, 1.13), and Seven (OR=1.18, 95% CI=1.10-1.27) significantly different from Pattern One. Arrival weight, gender, cumulative morbidity, risk code, and time were all determined to confound the relationship between temporal pattern and the probability of grading Choice or Prime within a cohort. All covariates considered for inclusion into the main effects model were statistically associated with the probability of Choice and Prime carcasses within a cohort.

The effect of temporal pattern on quality grades was modified by arrival weight, cumulative morbidity, and risk code (Table 6). Residual analysis demonstrated adequate model fit, and QIC indicated exchangeable correlation structure was appropriate for these data. In general, as arrival weight category decreased the percentage of Choice and Prime carcasses increased, but to a varying extent among temporal patterns (Figure 7). When assessing the interaction of temporal pattern and cumulative morbidity category it should be noted that there were no cohorts for Pattern Seven in the 10 to < 20% or ≥ 20% cumulative morbidity categories and thus those interactions could not be assessed (Table 6). The interactive effects of temporal pattern and cumulative morbidity on Choice and Prime carcasses appeared to be primarily driven by Pattern Six. For Pattern Six, the percentage of Choice and Prime carcasses within cattle cohorts decreased as cumulative morbidity increased; however, there appeared to be an increase in the percentage of Choice and Prime carcasses when moving from 10- < 20% cumulative morbidity cohorts to ≥ 20% morbidity cohorts in Pattern Six. The effect of temporal pattern on Choice and Prime carcasses was also significantly modified by respiratory risk code, but the magnitude of this interaction was small (Table 6).

Mortality risk

The bivariable model for the effect of temporal pattern on mortality risk indicated a significant association. Cohorts within Temporal Pattern Two displayed significantly higher mortality risk compared to cohorts in Pattern One (OR = 1.32, 95% CI = 1.20, 1.44). Cohorts in Patterns Four - Seven displayed significantly lower mortality than those in Pattern One with odd ratios ranging from 0.46 in Pattern Seven (95% CI=0.41, 0.53) to 0.84 in Pattern Four (95% CI=0.75, 0.94). Arrival weight, cumulative morbidity, risk code, and time were all determined to confound the relationship between temporal pattern and mortality risk. The main effects model indicated that all covariates (temporal pattern, gender, arrival weight, cumulative morbidity, risk code, time, and feedlot) were significantly associated with mortality risk.

In the final model, the effect of temporal pattern on mortality was modified by arrival weight and cumulative morbidity (Table 7). Residual analysis demonstrated adequate model fit, and QIC indicated exchangeable correlation structure was appropriate for these data. In general, as arrival weight category decreased, mortality risk increased, with the exception of cohorts in Pattern Five that were < 182 kg (Figure 8). In Pattern Six, the magnitude of the increase in mortality risk seemed much larger than for other patterns when moving from the 182-226 kg

71

weight category to < 182 kg (Figure 8). In addition, as cumulative morbidity increased, so did mortality risk (Table 7); however, the magnitude of the increase in higher morbidity categories appeared to be greater for temporal Patterns One and Two as compared to the other temporal patterns.

Retreatment risk

The bivariable model for the effect of temporal pattern on retreatment risk indicated a significant effect. Cattle cohorts in Temporal Pattern Two had a significantly increased risk of retreatment compared to cohorts in Temporal Pattern One (OR = 1.16, 95% CI = 1.05, 1.28). Cohorts in Temporal Patterns Four - Seven had lower retreatment risk compared to Temporal Pattern One, with odds ratios ranging from 0.52 in temporal Pattern Seven (95% CI=0.42, 0.64) to 0.81 in Temporal Pattern Four (95% CI=0.72, 0.91). Arrival weight, cumulative morbidity, risk code, and time were all determined to confound the relationships between temporal patterns and retreatment risk. In the main effects model, temporal pattern, gender, arrival weight, cumulative morbidity, risk code, time, and feedlot were all significant.

In the final model, there was significant effect modification of temporal pattern by both arrival weight and cumulative morbidity (Table 8). Residual analysis demonstrated adequate model fit, and QIC indicated exchangeable correlation structure was appropriate for these data. Figure 9 demonstrates the effect modification between temporal pattern and arrival weight categories. The interaction between temporal pattern and cumulative morbidity could not be computed for two categories (i.e., 10 to < 20% and ≥ 20%) within Temporal Pattern Seven because there were no cohorts with this covariate pattern. Except for Temporal Pattern Six, retreatment risk tended to be higher for cattle cohorts in higher cumulative morbidity categories.

Discussion

Feedlot veterinarians have stressed the importance of assessing temporal patterns of BRDC cases (Booker et al., 2004; Corbin and Griffin, 2006); however, ours is the first study to classify temporal patterns of BRDC cases within cohorts of commercial feedlot cattle and to identify significant associations with important cattle health and performance indices. Previously, others have descriptively assessed BRDC patterns within cohorts of feedlot cattle by observing epidemic curves (Woods et al., 1973; Martin, 1983; Smith et al., 2001). Displays of epidemic curves for ranch and auction-derived cattle showed that ranch-derived cattle had a

72

more gradual increase in the cumulative number of cases over time than did auction-derived cattle (Smith et al., 2001). Our results show that some cohorts of cattle have a large percent of their cases early in the risk period, some a more gradual increase, while others show a steep increase late in the 100-day risk period (Figure 2). We defined temporal patterns of BRDC using cumulative distributions in order to focus on the timing of disease occurrence rather than the magnitude of disease within a cohort of cattle. We've found that assessing both the temporal distribution and magnitude of disease burden simultaneously led to clusters driven almost exclusively by the latter (data not shown). However, we recognized that the magnitude, based on cumulative morbidity, could differ among temporal patterns and thus included cumulative morbidity as a covariate in multivariable models assessing the effects of temporal patterns on economically important production and health outcomes. Describing these temporal patterns is important because they may indicate certain disease processes or cattle demographics that influence when cases of BRDC occur and also may represent disease determinants that can be modified to mitigate BRDC. With BRDC viral pathogens may predispose the lung to bacterial infection, and these exposures may take place before or after arrival to the feedlot (Callan and Garry, 2002). The magnitude and timing of BRDC incidence in a cohorts could differ based on several predisposing factors including; animal age, stress, previous viral exposure or vaccination, nutrition, cohort source, commingling, and time in transit (Lechtenberg et al., 1998). Since clusters of BRDC temporal patterns within feedlot cohorts have not been previously demonstrated, the goal of our study was not to determine why temporal patterns occur. However, our results illustrate that different temporal patterns of BRDC cases do exist in feedlot cattle populations and they are associated with important cattle health and performance indices.

To our knowledge, hierarchical clustering methods have not been used to classify temporal patterns of feedlot disease events. Hierarchical clustering methods are useful for classifying disease patterns, as similar distributions can be combined into groups (i.e., "clusters") such that the temporal distributions of BRDC cases within cohorts in each cluster are more similar than distributions in other clusters. Ward's method was chosen over other hierarchical clustering techniques because it is relatively efficient computationally, and the similarities to ANOVA provide ease in interpretation. With Ward's method the ESS (and corresponding height values) are smaller when more clusters are included, but always increase to some extent (as seen, moving right to left, in Figure 1) when clusters are combined. However, these values will

increase dramatically when two dissimilar clusters are combined; thus, a relatively large increase indicates that the number of clusters should not be reduced (Ward, 1963). Although optimizing the number of clusters with Ward's method is somewhat subjective, results in Figure 1 seem to clearly demonstrate that seven clusters provide optimal fit for our data (Figure 1).

Criteria for diagnosing BRDC in the feedlot industry are commonly based on subjective clinical signs. General criteria for identification of BRDC cases include depression, elevated respiratory rate or labored respiration, and elevated body temperature (Sanderson et al., 2008). Our case definition for BRDC in this study was broad (animal diagnosed by feedlot personnel as having BRDC and thereafter treated with an antimicrobial), but based on consistently available data. This case definition may lead to misclassification of both sick and healthy cattle, as White and Renter (2009) have showed both sensitivity (62%) and specificity (63%) of diagnosing BRDC using clinical criteria are relatively low. There is also potential for differential bias, which can be common in large observational studies if the clinical case definitions between feedlots are also related to the feedlots' management practices (Sanderson et al., 2008). However, this is the industry standard for diagnosing BRDC and we are simply reporting a measure of treatment risk, which is based on perceived morbidity (Sanderson et al., 2008). We also added both time of arrival and feedlot as parameters to account for unmeasured differences in management practices among feedlots and over time. There is a lack of consistent standardized reporting of data across feedlots in the United States (Corbin and Griffin, 2006). Beyond a few general risk factors (arrival weight, arrival time, and gender) there are limited data recorded in consistent fashion across feedlots; this makes it difficult to provide a more comprehensive assessment of risk factors. In our multivariable analyses, we were unable to account for factors such as preconditioned status (vaccination and weaning strategy), source of cattle, distance traveled, temperament of cattle, and nutritional status at arrival, which are all thought to have an association with BRDC (Duff and Galyean, 2007). However, we did include a variable indicating respiratory risk code, which might be considered a summary, proxy variable for many of these factors (Lechtenberg et al. 1998). Our analysis included only nine commercial feedlots, all located in one region of the U.S., so generalizations across the industry may be limited. However, participating feedlots contained cattle and used production practices that were typical of U.S. feedlots.

The effect of BRDC on economically important performance and health measures is well documented (Wittum et al., 1996; Gardner et al., 1999; Busby and Strohbehn, 2004; Irsik et al., 2006). However, few studies have assessed how the timing of BRDC affects cattle performance and health, and those studies used individual animal data (Thompson et al., 2006; Babcock et al., 2009). Both studies found an association between the timing of BRDC treatment and several performance and health outcomes. In our current study, the assessment of the cumulative distribution of cases may have seemed trivial to those in the feedlot industry had we not documented economically important performance and health differences among temporal patterns. One important measure of general efficiency of feedlot cattle is mean daily weight gain (Smith et al., 2001). We found that daily gain differed across temporal patterns and that the effect was modified by arrival weight and respiratory risk code. These findings agree with Babcock et al. (2009) who found (using individual animal data) the effect of the timing of BRDC treatment on weight gain was modified by arrival weight. Despite a statistically significant interaction between the two factors, we found that the magnitude of mean daily weight gain was relatively consistent between high and low risk cohorts across temporal patterns, with low risk cohorts having higher daily weight gain (Figure 3). The exception was for Temporal Pattern One where estimates between high and low risk cohorts appeared to be very similar; perhaps indicating that the disease processes which result in a quick accumulation of cases within cohorts impact weight gain irrespective of arrival risk factors. The similar mean daily weight gain in Pattern One also could be due to misclassification of low risk cohorts, since both low and high risk cohorts are accumulating BRDC cases soon after arrival in Pattern One.

Temporal pattern was significantly associated with days on feed, another economically important indicator of cattle performance, but that effect was modified by arrival weight and risk code. The magnitude of the effect of temporal pattern was very small, and there were only small differences in days on feed between temporal patterns within arrival weight categories (Figure 4); these effects likely would not be economically relevant for most producers. Although Babcock et al. (2009) assessed days on feed for individual animals and not an average for the cohort, they too found very small differences in days on feed based on when animals were diagnosed and treated for BRDC.

Feedlots frequently market cattle utilizing grid pricing, where the price paid is a function of carcass characteristics such as weight, yield grade, and quality grade (Mintert, 2003).

Therefore, it is increasingly important for feedlots to market cattle with ideal carcass characteristics (e.g., Yield Grade One or Two, Quality Grade Choice and Prime) as premiums are added to the base price of a carcass. Our results showed differences in carcass weight, yield grade, and quality grade among cohorts with different BRDC temporal patterns while accounting for additional covariates. These results support some findings of Babcock et al. (2009), who found differences in carcass weight based on the timing of BRDC treatment, but found little to no difference in yield and quality grades. However, it is important to consider that their results were based on individual animal data, and not cohort-level data. They assessed the timing of BRDC treatment based on the week in the feedlot that animals became a case and then compared individual carcass data (Babcock et al., 2009). Our study used aggregated data with timing assessed as a cumulative distribution and carcass data as cohort means or proportions. Our study data prevent us from drawing inferences at the individual animal level; however, we are primarily interested in the cohort, the level at which most commercial feedlots manage and market cattle. Our current research is the first to show relationships between BRDC timing and important carcass characteristics at the cohort level.

The significant interactions in the model assessing carcass weights (Table 4) indicate these weights are differentially affected by BRDC temporal patterns depending on arrival characteristics of the cattle. After including other covariates, the largest differences in carcass weight between temporal patterns (across weight categories) occurred in temporal patterns with cases accumulating early and late in the study period (Temporal Patterns One and Seven; Figure 5). Although the cause of these differences is not directly apparent, other research has shown differences in carcass weight of individual animals based on BRDC timing, with effects modified by arrival weight (Babcock et al., 2009). The effects of risk code are hard to compare across disparate studies because of varying definitions for these classifications. For cohorts where cases accumulated early (Temporal Patterns One – Three), low risk cohorts appeared to have heavier carcass weights compared to high risk cohorts; however, there appears to be no differential effects for Temporal Patterns Four – Seven. These results seem biologically plausible, as increased morbidity has been found to be associated with lower carcass weights in individual animals (Gardner et al., 1999), and thus high risk cohorts could have lower mean carcass weights.

Male cohorts tended to have a decrease in the percentage of Yield Grade One and Two carcasses when moving sequentially from Temporal Patterns One to Seven; however, female cohorts showed variable effects across temporal patterns (Figure 6). Across all temporal patterns, male cohorts displayed a higher percentage of Yield Grade One and Two carcasses than female cohorts. Others have found that heifers have a higher percentage of kidney, pelvic, and heart fat, and a higher percentage of total fat removed during fabrication; factors that could contribute to a lower percentage of Yield Grade One and Two carcasses (Dillion, 2009). The differential effects of temporal patterns with female cohorts was unexpected, and not described previously in the literature.

We found that across most temporal patterns the percentage of Choice and Prime carcasses tended to increase as arrival weight decreased (Figure 7), which is consistent with literature indicating that cattle placed on feed at younger ages (a proxy for weight) results in greater intramuscular fat and inherently results in a greater percentage of Choice or above carcasses (Schoonmaker et al., 2002). The decreased percentage of Choice and Prime carcasses across most temporal patterns as cumulative morbidity category increased seems biologically plausible as adverse health outcomes at the individual-animal level have been shown to negatively affect quality grades (Gardner et al., 1999; Reinhardt et al., 2009; Schneider et al., 2009).

Differences in additional adverse health outcomes (mortality risk and retreatment risk) were fairly pronounced across different BRDC temporal patterns. While controlling for other covariates and modeling the effect modification due to arrival weight and cumulative morbidity, differences in mortality risk across temporal patterns were still evident. Others have found few differences in mortality based on when individual animals were treated for BRDC (Babcock et al., 2009). For most temporal patterns, increasing arrival weight categories were associated with slight increases in cumulative mortality; this agrees with literature documenting mortality differences across arrival weights (Loneragan, 2004). The reason for this increased risk is thought to be associated with the age/maturity, source of cattle, previous management, and the amount of commingling prior to arrival (Smith et al., 2001). Lighter weight cohorts can be freshly weaned, stressed animals with suppressed immune systems (Lechtenberg et al., 1998). However, the negative association between weight category and mortality was not seen in all temporal patterns. In Temporal Patterns Five and Six there were unexpected increases and

decreases in risk when weight class increased (Figure 8); effects that require further research into biological mechanisms. There were also differential effects of temporal patterns across cumulative morbidity categories, as increases in mortality risk occurred when BRDC occurred early (e.g., Temporal Patterns One and Two) and morbidity was high (> 20 percent). Some research indicates that for every one percent increase in the number of animals treated for BRDC, death loss increased by 0.14% on an absolute scale (Irsik et al., 2006). These results support our findings of increased cumulative mortality for cohorts with high morbidity, but fail to explain why cohorts with early BRDC (Temporal Patterns One and Two) and high morbidity appeared to have greater cumulative mortality as compared to other temporal patterns. Differences in retreatment risk that we identified were consistent with those described previously (Babcock et al., 2009). Like our current cohort-level study, that individual animal-level study found BRDC timing and retreatment risk to be strongly associated. In both studies, there was a tendency for animals or cohorts with early BRDC to have a greater risk for retreatment, although in our current study this effect was modified by arrival weight and cumulative morbidity. The increased retreatment risk may be due, at least in part, to the fact that cohorts with BRDC early have greater time at risk for retreatment. This also could explain why the effect of temporal pattern was modified by arrival weight, since lighter weight cattle would have more days in the feedlot and thus more potential time for retreatment. However, most BRDC cases in our study population occurred during the study period (first 100 days following arrival); including 95.2% of initial cases and 97.1% of cattle that were retreated (data not shown). In addition, only Temporal Pattern Three, and perhaps Temporal Patterns Two and Four (to a lesser extent), showed a consistent increase in retreatment risk for lighter weight cattle. For the other temporal patterns of BRDC, the retreatment risk varied little or appeared to decrease when cattle were lighter; perhaps indicating different BRDC disease processes reflected by the different temporal patterns. The modification of temporal pattern effects by cumulative morbidity may be due, at least in part, to the data and variable specification – i.e., cumulative morbidity reflected the magnitude of disease burden in the population and thus the number of cattle eligible (at risk) for retreatment. This resulted in a positive association between these variables, the magnitude of which differed slightly among some temporal patterns.

Conclusion

We identified seven temporal patterns (clusters) of BRDC cases within cohorts of commercial feedlot cattle and found that these temporal patterns were associated with important animal performance and health indices. Although the temporal patterns were associated with adverse performance and health, it would be difficult to broadly classify and summarize the adverse effects as they were often modified across gender, weight, risk class, and cumulative morbidity category. To answer specific questions regarding differential performance and health outcomes among cattle with different BRDC temporal patterns, specific covariate patterns from multivariable models must be considered. Further research on the epidemiologic mechanisms related to temporal patterns of BRDC is warranted.

Acknowledgements

References

Babcock, A.H., White, B.J., Dritz, S.S., Thomson, D.U., Renter, D.G., 2009. Feedlot health and performance effects associated with the timing of respiratory disease treatment. J. Anim. Sci. 87, 314-327.

Booker, C.W., Loneragan, G.H., Guichon, P.T., Kee, J.G., Schunicht, O.C., Wildman, B.K., Pittman, T.J., Fenton, R.K., Janzen, E.D., Perrett, T., 2004. Practical Application of Epidemiology in Veterinary Herd Health/production Medicine. In, AABP Proceedings, pp. 59-62.

Busby, W.D., Strohbehn, D.R., 2004. Effect of postweaning health on Feedlot Performance and Quality Grade. Iowa State University Animal Industry Report 2004.

Corbin, M.J., Griffin, D., 2006. Assessing performance of feedlot operations using epidemiology. Vet. Clin. North Am. Food Anim. Pract. 22, 35-51.

Cusack, P., McMeniman, N., Lean, I., 2003. The medicine and epidemiology of bovine respiratory disease in feedlots. Aust. Vet. J. 81, 480-487.

Dillion, J.T., 2009. Evaluating the impacts of gender, fatness, muscling, and weight on yield grade 4 beef carcasses. Texas A&M University. <http://hdl.handle.net/1969.1/ETD-TAMU-2009-08-902> (last accessed 6.1.2010).

Dohoo, I., Martin, W., Stryhm, H., 2003a. Logistic Regression. Veterinary Epidemiologic Research. Charlottetown, Prince Edward Island, pp. 335-372.

Dohoo, I., Martin, W., Stryhm, H., 2003b. Mixed Models for Continuous Data. Veterinary Epidemiologic Research. AVC Inc., Charlottetown, Prince Edward Island, pp. 473-498.

Dohoo, I., Martin, W., Stryhm, H., 2003c. Model-building strategies. Veterinary Epidemiologic Research. AVC Inc., Charlottetown, Prince Edward Island, pp. 317-334.

Duff, G.C., Galyean, M.L., 2007. Board-invited review: recent advances in management of highly stressed, newly received feedlot cattle. J. Anim. Sci. 85, 823-840.

Edwards, A.J., 1996. Respiratory diseases of feedlot cattle in the central USA. Bov. Pract. 30, 5-7.

Gardner, B.A., Dolezal, H.G., Bryant, L.K., Owens, F.N., Smith, R.A., 1999. Health of finishing steers: effects on performance, carcass traits, and meat tenderness. J. Anim. Sci. 77, 3168-3175.

Gay, E., Barnouin, J., 2009. A nation-wide epidemiological study of acute respiratory disease in France. Prev. Vet. Med. 89, 265-271.

Griffin, D., 1997. Economic Impact Associated with Respiratory Disease in Beef Cattle. Vet. Clin. North Am. Food Anim. Pract. 13, 367-377.

Griffin, D., 1998. Feedlot Diseases. Vet. Clin. North Am. Food Anim. Pract. 14, 199-231.

Hardin, J.W., Hilbe, J.M., 2003. Residuals, diagnostics, and testing. Generalized estimating equations. Chapman & Hall/CRC., Boca Raton, FL, pp. 137-179.

Irsik, M., Langemeier, M., Schroeder, T., Spire, M., Roder, J.D., 2006. Estimating the Effects of Animal Health on the Performance of Feedlot Cattle. Bov. Pract. 40, 65-74.

Lechtenberg, K.F., Smith, R.A., Stokka, G.L., 1998. Feedlot Health and Management. Vet. Clin. North Am. Food Anim. Pract. 14, 177-197.

Loneragan, G.H., 2004. Feedlot mortalities: epidemiology, trends, classification. In, Academy of Veterinary Consultants Summer Meeting, 32(3) 34-43.

Martin, S.W., Meek, A.H., Davis, D.G., Johnson, J.A., Curtis, R.A., 1982. Factors associated with mortality and treatment costs in feedlot calves: the Bruce County Beef Project, years 1978, 1979, 1980. Can. J. Comp. Med. 46, 341-349.

Martin, S.W., 1983. Factors influencing morbidity and mortality in feedlot calves in Ontario. Vet. Clin. North Am. Large Anim. Pract. 5, 73.

Mintert, J., 2003. Beef feedlot industry. Vet. Clin. North Am. Food Anim. Pract. 19, 387-395.

Norstrom, M., Pfeiffer, D.U., Jarp, J., 1999. A space-time cluster investigation of an outbreak of acute respiratory disease in Norwegian cattle herds. Prev. Vet. Med. 47, 107-119.

Reinhardt, C.D., Busby, W.D., Corah, L.R., 2009. Relationship of various incoming cattle traits with feedlot performance and carcass traits. J. Anim. Sci. 87, 3030-3042.

R, 2010. R documentation. <http://stat.ch/R-manual/R-patched/library/stats/html/hclust.html> (last accessed 02.15.10).

Ribble, C.S., Meek, A.H., Janzen, E.D., Guichon, P.T., Jim, G.K., 1995. Effect of time of year, weather, and the pattern of auction market sales on fatal fibrinous pneumonia (shipping fever) in calves in a large feedlot in Alberta (1985-1988). Can. J. Vet. Res. 59, 167-172.

Sanderson, M.W., Dargatz, D.A., Wagner, B.A., 2008. Risk factors for initial respiratory disease in United States' feedlots based on producer-collected daily morbidity counts. Can. Vet. J. 49, 373-378.

Schneider, M.J., Tait, R.G., Jr., Busby, W.D., Reecy, J.M., 2009. An evaluation of bovine respiratory disease complex in feedlot cattle: Impact on performance and carcass traits using treatment records and lung lesion scores. J. Anim. Sci. 87, 1821-1827.

Schoonmaker, J.P., Loerch, S.C., Fluharty, F.L., Zerby, H.N., Turner, T.B., 2002. Effect of age at feedlot entry on performance and carcass characteristics of bulls and steers. J. Anim. Sci. 80, 2247-2254.

Scott, H.M., Soskolne, C.L., Martin, S.W., Shoukri, M.M., Lissemore, K.D., Coppock, R.W., Guidotti, T.L., 2003. Air emissions from sour-gas processing plants and dairy-cattle reproduction in Alberta, Canada. Prev. Vet. Med. 57, 69-95.

Smith, R.A., 1998. Impact of disease on feedlot performance: a review. J. Anim. Sci. 76, 272-274.

Smith, R.A., Stokka, G.L., Radostits, O.M., D.D.Griffin, 2001. Health and Production Management in Beef Feedlots. In: Radostits, O.M. (Ed.), Herd Health: Food Animal Production Medicine. W.B. Saunders Company, Philadelphia, pp. 581-633.

Thompson, P.N., Stone, A., Schultheiss, W.A., 2006. Use of treatment records and lung lesion scoring to estimate the effect of respiratory disease on growth during early and late finishing periods in South African feedlot cattle. J. Anim. Sci. 84, 488-498.

USDA:AMS, 1997. United States Standards for Grades of Carcass Beef. Livestock and Seed Divisioin, Washington, DC. <http://www.ams.usda.gov/AMSv1.0/getfile?dDocName=STELDEV3002979> (last accessed 09.15.2009).

Vogel, G.J., Parrott, C., 1994. Mortality Survey in Feedyards: The Incldence of Death from Digestive, Respiratory, and Other Causes in Feedyards on the Great Plains. Food Anim. Comp. 16, 227-234.

Ward, J.H., 1963. Hierachical grouping to optimize an objective function. J. Am. Statist. Assoc. 58, 236-244.

White, B.J., Renter, D.G., 2009. Bayesian estimation of the performance of using clinical observations and harvest lung lesions for diagnosing bovine respiratory disease in post-weaned beef calves. J. Vet. Diagn. Invest. 21, 446-453.

Wittum, T.E., Woollen, N.E., Perino, L.J., Littledike, E.T., 1996. Relationships among treatment for respiratory tract disease, pulmonary lesions evident at slaughter, and rate of weight gain in feedlot cattle. J. Am. Vet. Med. Assoc. 209, 814-818.

Woods, G.T., Mansfield, M.E., Webb, R.J., 1973. A three year comparison of acute respiratory disease, shrink and weight gain in preconditioned and non-preconditioned Illinois beef calves sold at the same auction and mixed in a feedlot. Can. J. Comp. Med. 37, 249.

Table 3.1 Frequency distribution of feedlot cattle cohorts (n = 7,553) by potential risk factors and temporal patterns of bovine respiratory disease complex (BRDC)

Variable	Variable Level	Temporal pattern[a]							
		1	2	3	4	5	6	7	Total
Arrival weight (kg)	≥ 409	0.7	0.8	0.5	0.2	0.4	0.5	0.3	3.4
	363-408	2.7	3.1	3.2	1.2	3.2	2.5	1.2	17.2
	318-362	5.3	6.2	6.0	2.4	5.6	4.4	1.7	31.6
	272-317	5.0	5.8	4.3	1.9	4.1	2.4	1.0	24.5
	227-271	2.8	4.2	2.7	1.0	2.2	1.4	0.6	14.8
	182-226	1.2	2.6	1.3	0.5	0.9	0.6	0.1	7.2
	<182	0.4	0.5	0.2	0.1	0.1	0.0	0.0	1.3
Total		18	23	18	7	17	12	5	100
Gender	Male	13.7	16.3	12.8	5.5	12.1	8.6	3.8	72.8
	Female	4.4	6.9	5.5	1.6	4.4	3.1	1.2	27.1
Total		18	23	18	7	17	12	5	100
Cumulative morbidity category	0 - <5%	7.4	8.8	11.4	2.9	9.9	9.4	5.0	54.8
	5 - <10%	3.8	4.2	2.7	2.2	4.0	1.6	0.1	18.6
	10 - <20%	3.3	4.5	2.0	1.4	2.1	0.6	0.0	13.9
	≥ 20%	3.7	5.8	2.2	0.6	0.6	0.1	0.0	13.0
Total		18	23	18	7	17	12	5	100
Risk code	Low	12.3	13.8	13.5	5.5	13.1	10.1	4.7	73.0
	High	5.8	9.4	4.7	1.7	3.5	1.6	0.3	27.0
Total		18	23	18	7	17	12	5	100

Table 3.2 Final multivariable linear mixed model (with feedlot as a random effect[a]) for mean weight gain in kg/animal/day for feedlot cattle cohorts (n = 7,553)

Covariate	LR Test	Levels	b	S.E. (b)	95% CI	
Intercept			1.46	0.04	1.39	1.53
Temporal pattern	0.7932	1	Referent			
		2	-0.04	0.02	-0.08	0.01
		3	-0.01	0.03	-0.06	0.04
		4	-0.01	0.04	-0.08	0.07
		5	-0.01	0.03	-0.07	0.05
		6	-0.01	0.03	-0.06	0.04
		7	0.00	0.03	-0.06	0.06
Arrival weight (kg)	<0.0001	≥ 409	Referent			
		363-408	-0.04	0.02	-0.08	0.00
		318-362	-0.05	0.02	-0.09	-0.01
		272-317	-0.10	0.02	-0.14	-0.07
		227-271	-0.19	0.02	-0.22	-0.15
		182-226	-0.29	0.02	-0.33	-0.25
		<182	-0.33	0.03	-0.39	-0.28
Risk code	0.9518	Low	Referent			
		High	0.00	0.01	-0.02	0.02
Temporal pattern X	0.0212	1 X ≥ 409	Referent			
Arrival weight		1 X 363-408	Referent			
		1 X 318-362	Referent			
		1 X 272-317	Referent			
		1 X 227-271	Referent			
		1 X 182-226	Referent			
		1 X <182	Referent			
		2 X ≥ 409	Referent			
		2 X 363-408	0.03	0.03	-0.02	0.08
		2 X 318-362	0.03	0.03	-0.02	0.08
		2 X 272-317	0.03	0.02	-0.02	0.08
		2 X 227-271	0.04	0.03	-0.01	0.09
		2 X 182-226	0.07	0.03	0.01	0.12
		2 X <182	0.07	0.04	0.00	0.15
		3 X ≥ 409	Referent			
		3 X 363-408	0.02	0.03	-0.03	0.08
		3 X 318-362	-0.01	0.03	-0.06	0.05
		3 X 272-317	0.02	0.03	-0.03	0.08
		3 X 227-271	0.03	0.03	-0.03	0.08
		3 X 182-226	0.07	0.03	0.01	0.13
		3 X <182	-0.02	0.05	-0.11	0.07
		4 X ≥ 409	Referent			

		4 X 363-408	0.03	0.04	-0.05	0.11
		4 X 318-362	0.00	0.04	-0.08	0.08
		4 X 272-317	0.01	0.04	-0.07	0.09
		4 X 227-271	0.01	0.04	-0.08	0.09
		4 X 182-226	0.09	0.05	0.00	0.18
		4 X <182	0.01	0.06	-0.11	0.14
		5 X ≥ 409	Referent			
		5 X 363-408	0.03	0.03	-0.03	0.10
		5 X 318-362	0.02	0.03	-0.04	0.07
		5 X 272-317	0.02	0.03	-0.04	0.08
		5 X 227-271	0.01	0.03	-0.05	0.07
		5 X 182-226	0.05	0.03	-0.02	0.12
		5 X <182	0.09	0.06	-0.02	0.20
		6 X ≥ 409	Referent			
		6 X 363-408	0.02	0.03	-0.04	0.07
		6 X 318-362	0.02	0.03	-0.04	0.07
		6 X 272-317	0.04	0.03	-0.02	0.09
		6 X 227-271	0.01	0.03	-0.05	0.07
		6 X 182-226	0.05	0.04	-0.02	0.12
		6 X <182	0.00	0.08	-0.16	0.15
		7 X ≥ 409	Referent			
		7 X 363-408	0.03	0.03	-0.04	0.10
		7 X 318-362	0.04	0.03	-0.03	0.10
		7 X 272-317	0.02	0.03	-0.05	0.09
		7 X 227-271	0.00	0.04	-0.07	0.08
		7 X 182-226	-0.06	0.05	-0.17	0.04
		7 X <182	0.00	0.08	-0.16	0.16
Temporal pattern X Risk code	0.0137	1 X Low	Referent			
		2 X Low	Referent			
		3 X Low	Referent			
		4 X Low	Referent			
		5 X Low	Referent			
		6 X Low	Referent			
		7 X Low	Referent			
		1 X High	Referent			
		2 X High	-0.02	0.01	-0.05	0.00
		3 X High	-0.04	0.01	-0.07	-0.02
		4 X High	-0.04	0.02	-0.07	0.00
		5 X High	-0.04	0.01	-0.07	-0.01
		6 X High	-0.04	0.02	-0.07	-0.01
		7 X High	-0.02	0.03	-0.08	0.03
Gender[b]	<0.0001					
Cumulative morbidity[b]	<0.0001					

Time[b]	<0.0001

Table 3.3 Final multivariable linear mixed model (with feedlot as a random effect[a]) for mean days on feed for feedlot cattle cohorts (n = 7,553)

Covariate	LR Test	Levels	b	S.E. (b)	95% CI	
Intercept			128.79	4.82	119.35	138.22
Temporal pattern	0.4228	1	Referent			
		2	1.97	3.27	-4.44	8.38
		3	8.07	3.56	1.09	15.04
		4	1.71	5.22	-8.51	11.94
		5	4.44	3.98	-3.36	12.25
		6	2.26	3.65	-4.90	9.42
		7	4.48	4.27	-3.88	12.84
Arrival weight (kg)	<0.0001	≥409	Referent			
		363-408	25.08	2.67	19.84	30.31
		318-362	46.11	2.53	41.16	51.06
		272-317	73.23	2.48	68.38	78.09
		227-271	109.05	2.59	103.98	114.12
		182-226	150.30	2.90	144.62	155.97
		<182	206.17	3.92	198.49	213.86
Risk code	<0.0001	Low	Referent			
		High	7.22	1.17	4.93	9.52
Temporal pattern X	<0.0001	1 X ≥ 409	Referent			
Arrival weight		1 X 363-408	Referent			
		1 X 318-362	Referent			
		1 X 272-317	Referent			
		1 X 227-271	Referent			
		1 X 182-226	Referent			
		1 X <182	Referent			
		2 X ≥ 409	Referent			
		2 X 363-408	-1.42	3.62	-8.52	5.68
		2 X 318-362	-0.27	3.42	-6.98	6.44
		2 X 272-317	-2.76	3.37	-9.37	3.84
		2 X 227-271	0.91	3.48	-5.92	7.73
		2 X 182-226	-5.50	3.79	-12.93	1.93
		2 X <182	-13.31	5.27	-23.64	-2.99
		3 X ≥ 409	Referent			
		3 X 363-408	-8.98	3.87	-16.57	-1.39
		3 X 318-362	-6.94	3.70	-14.19	0.32
		3 X 272-317	-9.36	3.71	-16.63	-2.10
		3 X 227-271	-7.16	3.88	-14.77	0.45
		3 X 182-226	-11.72	4.30	-20.15	-3.29
		3 X <182	-9.28	6.38	-21.77	3.22
		4 X ≥ 409	Referent			
		4 X 363-408	-1.75	5.60	-12.74	9.23
		4 X 318-362	0.10	5.40	-10.48	10.69
		4 X 272-317	-2.15	5.42	-12.76	8.46
		4 X 227-271	-3.33	5.65	-14.41	7.76
		4 X 182-226	-17.00	6.22	-29.20	-4.81
		4 X <182	-9.59	8.81	-26.85	7.67
		5 X ≥ 409	Referent			
		5 X 363-408	-5.20	4.26	-13.56	3.16
		5 X 318-362	-3.52	4.12	-11.59	4.55

		5 X 272-317	-5.72	4.10	-13.77	2.32
		5 X 227-271	-2.78	4.28	-11.17	5.61
		5 X 182-226	-5.28	4.73	-14.55	3.98
		5 X <182	-28.21	7.73	-43.35	-13.06
		6 X ≥ 409	Referent			
		6 X 363-408	-1.37	4.00	-9.22	6.47
		6 X 318-362	-2.46	3.83	-9.97	5.05
		6 X 272-317	-2.92	3.92	-10.61	4.77
		6 X 227-271	-2.55	4.16	-10.70	5.61
		6 X 182-226	5.62	4.81	-3.80	15.05
		6 X <182	-26.49	10.81	-47.68	-5.31
		7 X ≥ 409	Referent			
		7 X 363-408	-6.66	4.72	-15.91	2.59
		7 X 318-362	-6.97	4.56	-15.92	1.97
		7 X 272-317	-9.37	4.71	-18.60	-0.13
		7 X 227-271	-6.33	5.01	-16.15	3.49
		7 X 182-226	11.84	7.08	-2.03	25.72
		7 X <182	23.07	11.18	1.15	44.98
Temporal pattern X Risk code	0.001	1 X Low	Referent			
		2 X Low	Referent			
		3 X Low	Referent			
		4 X Low	Referent			
		5 X Low	Referent			
		6 X Low	Referent			
		7 X Low	Referent			
		1 X High	Referent			
		2 X High	2.51	1.52	-0.47	5.48
		3 X High	6.02	1.69	2.71	9.34
		4 X High	4.58	2.29	0.08	9.08
		5 X High	2.70	1.77	-0.77	6.18
		6 X High	7.52	2.20	3.21	11.83
		7 X High	-3.41	3.87	-11.00	4.18
Gender[b]	<0.0001					
Cumulative morbidity[b]	0.0121					
Time[b]	<0.0001					

[a]Random effect for feedlot ($P < 0.01$); 5.1 percent of the variance came from between feedlots and 94.9 percent within feedlots

[b]Estimates for temporal pattern and its interactions were adjusted for gender, cumulative morbidity, and time (coefficients not shown, but are available from the authors on request)

Table 3.4 Final multivariable linear mixed model (with feedlot as a random effect[a]) for mean carcass weight in kg for feedlot cattle cohorts (n = 7,447)

Covariate	LR Test	Levels	b	S.E. (b)	95% CI	
Intercept			391.83	30.22	332.60	451.06
Temporal pattern	0.0489	1	Referent			
		2	-12.81	20.68	-53.34	27.71
		3	40.10	22.31	-3.62	83.82
		4	-7.48	32.71	-71.60	56.63
		5	-21.31	24.97	-70.25	27.64
		6	-5.31	22.91	-50.22	39.60
		7	49.75	26.75	-2.68	102.18
Arrival weight (kg)	<0.0001	≥ 409	Referent			
		363-408	-31.63	16.77	-64.51	1.24
		318-362	-27.70	15.85	-58.76	3.36
		272-317	-27.48	15.53	-57.92	2.96
		227-271	-73.00	16.27	-104.88	-41.12
		182-226	-89.05	18.38	-125.08	-53.03
		<182	-87.47	24.58	-135.66	-39.29
Risk code	<0.0001	Low	Referent			
		High	56.80	7.38	42.34	71.27
Temporal pattern X	<0.0001	1 X ≥ 409	Referent			
Arrival weight		1 X 363-408	Referent			
		1 X 318-362	Referent			
		1 X 272-317	Referent			
		1 X 227-271	Referent			
		1 X 182-226	Referent			
		1 X <182	Referent			
		2 X ≥ 409	Referent			
		2 X 363-408	16.52	22.86	-28.29	61.33
		2 X 318-362	0.10	21.63	-42.29	42.48
		2 X 272-317	-12.73	21.28	-54.44	28.97
		2 X 227-271	26.47	22.03	-16.71	69.65
		2 X 182-226	11.04	24.11	-36.22	58.30
		2 X <182	34.49	33.27	-30.71	99.69
		3 X ≥ 409	Referent			
		3 X 363-408	-37.19	24.30	-84.81	10.44
		3 X 318-362	-36.99	23.22	-82.50	8.52
		3 X 272-317	-51.27	23.25	-96.83	-5.71
		3 X 227-271	-34.41	24.40	-82.23	13.41
		3 X 182-226	-7.34	27.21	-60.67	45.99
		3 X <182	14.66	39.98	-63.70	93.02
		4 X ≥ 409	Referent			
		4 X 363-408	16.37	35.15	-52.52	85.26

89

		4 X 318-362	0.20	33.88	-66.21	66.60
		4 X 272-317	-7.88	33.97	-74.46	58.69
		4 X 227-271	35.51	35.48	-34.04	105.05
		4 X 182-226	57.48	39.36	-19.66	134.62
		4 X <182	1.28	55.22	-106.96	109.51
		5 X ≥ 409	Referent			
		5 X 363-408	32.53	26.75	-19.90	84.96
		5 X 318-362	16.08	25.82	-34.53	66.69
		5 X 272-317	7.16	25.74	-43.30	57.62
		5 X 227-271	48.89	26.90	-3.84	101.62
		5 X 182-226	44.36	29.80	-14.05	102.77
		5 X <182	77.59	48.46	-17.39	172.56
		6 X ≥ 409	Referent			
		6 X 363-408	16.16	25.12	-33.07	65.39
		6 X 318-362	-3.08	24.05	-50.22	44.05
		6 X 272-317	-22.39	24.60	-70.61	25.82
		6 X 227-271	21.11	26.14	-30.13	72.35
		6 X 182-226	71.24	30.30	11.85	130.63
		6 X <182	-29.21	67.80	-162.09	103.67
		7 X ≥ 409	Referent			
		7 X 363-408	-46.32	29.61	-104.35	11.71
		7 X 318-362	-43.76	28.62	-99.85	12.33
		7 X 272-317	-73.17	29.61	-131.20	-15.14
		7 X 227-271	14.32	31.45	-47.32	75.96
		7 X 182-226	25.69	44.50	-61.52	112.91
		7 X <182	95.74	70.17	-41.80	233.27
Temporal pattern X Risk code	<0.0001	1 X Low	Referent			
		2 X Low	Referent			
		3 X Low	Referent			
		4 X Low	Referent			
		5 X Low	Referent			
		6 X Low	Referent			
		7 X Low	Referent			
		1 X High	Referent			
		2 X High	-26.32	9.60	-45.13	-7.51
		3 X High	-28.64	10.69	-49.60	-7.68
		4 X High	-46.26	14.52	-74.72	-17.80
		5 X High	-51.04	11.21	-73.02	-29.06
		6 X High	-5.99	13.93	-33.30	21.32
		7 X High	-84.13	24.78	-132.71	-35.56
Gender[b]	<0.0001					
Cumulative morbidity[b]	0.005					
Time[b]	<0.0001					

[a]Random effect for feedlot ($P < 0.01$); 5.2 percent of the variance came from between feedlots and 94.8 percent within feedlots

90

[b]Estimates for temporal pattern and its interactions were adjusted for gender, cumulative morbidity, and time (coefficients not shown, but are available from the authors on request)

Table 3.5 Final multivariable logistic regression model[a] of the probability of USDA Yield Grade One or Two carcasses within feedlot cattle cohorts (n = 7,447)

Covariate	$P > \chi^2$	Level	b	Robust S.E. (b)	OR	95% CI OR	
Intercept			0.91	0.11			
Temporal pattern	<0.0001	1	Referent				
		2	0.04	0.02	1.04	0.99	1.09
		3	-0.04	0.03	0.96	0.91	1.01
		4	-0.02	0.03	0.98	0.93	1.04
		5	-0.05	0.03	0.95	0.91	1.00
		6	-0.13	0.03	0.88	0.83	0.93
		7	-0.1	0.04	0.91	0.84	0.98
Gender	<0.0001	Male	Referent				
		Female	-0.25	0.03	0.78	0.73	0.83
Temporal pattern X	<0.0001	1 X Male	Referent				
Gender		2 X Male	Referent				
		3 X Male	Referent				
		4 X Male	Referent				
		5 X Male	Referent				
		6 X Male	Referent				
		7 X Male	Referent				
		1 X Female	Referent				
		2 X Female	-0.11	0.04	0.90	0.83	0.98
		3 X Female	-0.11	0.05	0.90	0.82	0.99
		4 X Female	0.02	0.06	1.02	0.90	1.16
		5 X Female	0.04	0.05	1.04	0.95	1.15
		6 X Female	0.15	0.05	1.16	1.05	1.29
		7 X Female	0.01	0.08	1.01	0.87	1.18
Arrival weight (kg)[b]	<0.0001						
Cumulative morbidity[b]	0.7578						
Risk code[b]	0.0029						
Time[b]	<0.0001						
Feedlot[b]	<0.0001						

[a]Model was estimated using a generalized estimating equation with cohort as a panel variable and a exchangeable correlation structure
[b]Estimates for temporal pattern and its interactions were adjusted for arrival weight, cumulative morbidity, risk code, time, and feedlot (coefficients not shown, but are available from the authors on request)

Table 3.6 Final multivariable logistic regression model[a] of the probability of USDA Quality Grad Choice or Prime carcasses within feedlot cattle cohorts (n = 7,447 cohorts)

Covariate	$P > \chi^2$	Level	b	Robust S.E. (b)	OR	95% CI OR	
Intercept			-0.92	0.16			
Temporal pattern	0.0165	1	Referent				
		2	-0.15	0.14	0.86	0.65	1.14
		3	0.20	0.14	1.23	0.93	1.61
		4	0.41	0.16	1.50	1.09	2.06
		5	0.02	0.14	1.02	0.77	1.34
		6	0.11	0.13	1.12	0.86	1.45
		7	0.28	0.14	1.33	1.01	1.74
Arrival weight (kg)	<0.0001	≥ 409	Referent				
		363-408	0.39	0.09	1.47	1.22	1.77
		318-362	0.48	0.09	1.61	1.35	1.93
		272-317	0.61	0.09	1.84	1.55	2.19
		227-271	0.77	0.09	2.15	1.79	2.59
		182-226	1.15	0.12	3.15	2.50	3.96
		<182	1.09	0.12	2.98	2.35	3.79
Cumulative morbidity	<0.0001	0 - <5%	Referent				
		5 - <10%	-0.18	0.04	0.84	0.77	0.91
		10 - <20%	-0.26	0.04	0.77	0.71	0.84
		≥ 20%	-0.45	0.05	0.64	0.58	0.70
Risk code	<0.0001	Low	Referent				
		High	-0.15	0.04	0.86	0.80	0.93
Temporal pattern X Arrival weight	<0.0001	1 X ≥ 409	Referent				
		1 X 363-408	Referent				
		1 X 318-362	Referent				
		1 X 272-317	Referent				
		1 X 227-271	Referent				
		1 X 182-226	Referent				
		1 X <182	Referent				
		2 X ≥ 409	Referent				
		2 X 363-408	0.10	0.15	1.11	0.83	1.49
		2 X 318-362	0.06	0.15	1.06	0.80	1.41
		2 X 272-317	0.07	0.14	1.07	0.81	1.42
		2 X 227-271	-0.01	0.15	0.99	0.74	1.33
		2 X 182-226	-0.23	0.17	0.80	0.57	1.11
		2 X <182	0.10	0.19	1.10	0.76	1.60
		3 X ≥ 409	Referent				
		3 X 363-408	-0.25	0.15	0.78	0.59	1.04
		3 X 318-362	-0.29	0.14	0.75	0.57	0.99
		3 X 272-317	-0.26	0.14	0.77	0.58	1.02
		3 X 227-271	-0.17	0.15	0.84	0.63	1.13

		3 X 182-226	-0.36	0.18	0.70	0.50	0.99
		3 X <182	-0.24	0.18	0.79	0.55	1.12
		4 X $\geq$ 409	Referent				
		4 X 363-408	-0.52	0.17	0.59	0.43	0.83
		4 X 318-362	-0.53	0.17	0.59	0.43	0.82
		4 X 272-317	-0.59	0.17	0.55	0.40	0.77
		4 X 227-271	-0.67	0.17	0.51	0.36	0.72
		4 X 182-226	-0.90	0.22	0.41	0.26	0.62
		4 X <182	-1.01	0.25	0.37	0.22	0.60
		5 X $\geq$ 409	Referent				
		5 X 363-408	-0.15	0.15	0.86	0.65	1.14
		5 X 318-362	-0.14	0.14	0.87	0.66	1.15
		5 X 272-317	-0.08	0.14	0.93	0.70	1.23
		5 X 227-271	0.02	0.15	1.02	0.76	1.37
		5 X 182-226	-0.34	0.18	0.71	0.50	1.00
		5 X <182	-0.58	0.25	0.56	0.34	0.92
		6 X $\geq$ 409	Referent				
		6 X 363-408	-0.16	0.14	0.85	0.64	1.12
		6 X 318-362	-0.12	0.14	0.89	0.68	1.16
		6 X 272-317	-0.22	0.14	0.80	0.61	1.06
		6 X 227-271	-0.16	0.15	0.85	0.64	1.15
		6 X 182-226	-0.54	0.18	0.58	0.41	0.83
		6 X <182	-0.31	0.23	0.73	0.46	1.16
		7 X $\geq$ 409	Referent				
		7 X 363-408	-0.30	0.15	0.74	0.55	0.99
		7 X 318-362	-0.20	0.15	0.82	0.61	1.09
		7 X 272-317	-0.16	0.15	0.85	0.64	1.14
		7 X 227-271	-0.44	0.16	0.65	0.47	0.89
		7 X 182-226	-0.62	0.26	0.54	0.32	0.91
		7 X <182	-0.61	0.43	0.54	0.23	1.27
Temporal pattern X Cumulative morbidity	0.0175	1 X 0 - <5%	Referent				
		1 X 5 - <10%	Referent				
		1 X 10 - <20%	Referent				
		1 X $\geq$ 10%	Referent				
		2 X 0 - <5%	Referent				
		2 X 5 - <10%	0.07	0.06	1.07	0.96	1.20
		2 X 10 - <20%	0.16	0.06	1.17	1.04	1.31
		2 X $\geq$ 20%	0.10	0.07	1.10	0.96	1.26
		3 X 0 - <5%	Referent				
		3 X 5 - <10%	0.11	0.06	1.11	0.99	1.25
		3 X 10 - <20%	0.02	0.07	1.02	0.89	1.17
		3 X $\geq$ 20%	0.19	0.08	1.20	1.03	1.41
		4 X 0 - <5%	Referent				
		4 X 5 - <10%	0.09	0.07	1.09	0.96	1.25

		4 X 10 - <20%	0.19	0.08	1.20	1.03	1.41
		4 X ≥ 20%	0.14	0.11	1.15	0.93	1.42
		5 X 0 - <5%	Referent				
		5 X 5 - <10%	0.10	0.06	1.10	0.99	1.23
		5 X 10 - <20%	0.06	0.07	1.06	0.92	1.22
		5 X ≥ 20%	0.00	0.11	1.00	0.80	1.26
		6 X 0 - <5%	Referent				
		6 X 5 - <10%	0.01	0.07	1.01	0.88	1.17
		6 X 10 - <20%	-0.02	0.11	0.98	0.79	1.20
		6 X ≥ 20%	0.42	0.18	1.52	1.06	2.18
		3 X 0 - <5%	Referent				
		7 X 5 - <10%	0.85	0.44	2.35	0.99	5.56
		7 X 10 - <20%	N/A [b]				
		7 X ≥ 20%	N/A [b]				
Temporal pattern X Risk code	0.0152	1 X Low	Referent				
		2 X Low	Referent				
		3 X Low	Referent				
		4 X Low	Referent				
		5 X Low	Referent				
		6 X Low	Referent				
		7 X Low	Referent				
		1 X High	Referent				
		2 X High	0.07	0.06	1.08	0.96	1.21
		3 X High	0.03	0.07	1.03	0.91	1.18
		4 X High	0.22	0.08	1.24	1.06	1.46
		5 X High	0.13	0.07	1.14	1.00	1.29
		6 X High	0.21	0.08	1.24	1.05	1.46
		7 X High	0.31	0.14	1.37	1.05	1.78
Gender[c]	<0.0001						
Time[c]	<0.0001						
Feedlot[c]	<0.0001						

[a]Model was estimated using a generalized estimating equation with cohort as a panel variable and a exchangeable correlation structure
[b]The interaction between temporal pattern and cumulative morbidity could not be computed because there were no cohorts with these covariate patterns
[c]Estimates for temporal pattern and its interactions were adjusted for gender, time, and feedlot (coefficients not shown, but are available from the authors on request)

Table 3.7 Final multivariable logistic regression model[a] of the cumulative mortality risk within feedlot cattle cohorts (n = 7,447)

Covariate	$P > \chi^2$	Level	b	Robust S.E. (b)	OR	95% CI OR	
Intercept			-5.06	0.19			
Temporal pattern	0.1531	1	Referent				
		2	0.19	0.17	1.21	0.87	1.69
		3	-0.25	0.23	0.78	0.50	1.22
		4	-0.06	0.26	0.94	0.57	1.57
		5	0.15	0.20	1.16	0.78	1.73
		6	-0.18	0.20	0.83	0.57	1.23
		7	-0.28	0.23	0.76	0.48	1.18
Arrival weight (kg)	0.0012	≥ 409	Referent				
		363-408	0.02	0.17	1.02	0.73	1.41
		318-362	0.12	0.14	1.13	0.86	1.48
		272-317	-0.01	0.13	0.99	0.76	1.28
		227-271	0.04	0.14	1.04	0.79	1.37
		182-226	0.40	0.16	1.49	1.09	2.05
		<182	0.44	0.18	1.55	1.08	2.22
Cumulative morbidity	<0.0001	0 - <5%	Referent				
		5 - <10%	0.42	0.08	1.52	1.30	1.77
		10 - <20%	0.99	0.08	2.70	2.31	3.17
		≥ 20%	1.77	0.09	5.88	4.90	7.04
Temporal pattern X Arrival weight	0.0005	1 X ≥ 409	Referent				
		1 X 363-408	Referent				
		1 X 318-362	Referent				
		1 X 272-317	Referent				
		1 X 227-271	Referent				
		1 X 182-226	Referent				
		1 X <182	Referent				
		2 X ≥ 409	Referent				
		2 X 363-408	-0.11	0.21	0.89	0.60	1.34
		2 X 318-362	-0.08	0.18	0.93	0.66	1.31
		2 X 272-317	0.10	0.17	1.11	0.79	1.56
		2 X 227-271	0.15	0.18	1.16	0.82	1.66
		2 X 182-226	0.02	0.20	1.02	0.69	1.52
		2 X <182	-0.02	0.23	0.98	0.62	1.55
		3 X ≥ 409	Referent				
		3 X 363-408	0.31	0.26	1.36	0.82	2.24
		3 X 318-362	0.26	0.24	1.30	0.82	2.07
		3 X 272-317	0.61	0.24	1.83	1.15	2.92
		3 X 227-271	0.63	0.25	1.87	1.16	3.03
		3 X 182-226	0.32	0.26	1.37	0.82	2.29
		3 X <182	0.74	0.30	2.09	1.16	3.75

		4 X ≥ 409	Referent				
		4 X 363-408	0.20	0.29	1.22	0.69	2.15
		4 X 318-362	0.25	0.27	1.28	0.76	2.17
		4 X 272-317	0.34	0.27	1.40	0.83	2.37
		4 X 227-271	0.49	0.27	1.63	0.95	2.78
		4 X 182-226	0.01	0.29	1.01	0.57	1.78
		4 X <182	0.38	0.34	1.46	0.75	2.86
		5 X ≥ 409	Referent				
		5 X 363-408	0.02	0.23	1.02	0.65	1.61
		5 X 318-362	0.01	0.21	1.01	0.67	1.53
		5 X 272-317	0.26	0.21	1.29	0.86	1.95
		5 X 227-271	0.33	0.22	1.39	0.91	2.13
		5 X 182-226	0.13	0.24	1.13	0.71	1.81
		5 X <182	-0.60	0.35	0.55	0.27	1.10
		6 X ≥ 409	Referent				
		6 X 363-408	0.29	0.23	1.33	0.85	2.09
		6 X 318-362	0.30	0.21	1.35	0.90	2.02
		6 X 272-317	0.43	0.21	1.54	1.02	2.32
		6 X 227-271	0.65	0.22	1.91	1.25	2.93
		6 X 182-226	0.46	0.24	1.58	0.99	2.54
		6 X <182	0.96	0.27	2.61	1.55	4.39
		7 X ≥ 409	Referent				
		7 X 363-408	0.12	0.27	1.13	0.67	1.90
		7 X 318-362	0.05	0.25	1.05	0.64	1.70
		7 X 272-317	0.52	0.25	1.69	1.04	2.74
		7 X 227-271	0.38	0.27	1.46	0.86	2.49
		7 X 182-226	0.29	0.29	1.33	0.75	2.35
		7 X <182	0.55	0.43	1.73	0.75	3.99
Temporal pattern X Cumulative morbidity	0.0001	1 X 0 - <5%	Referent				
		1 X 5 - <10%	Referent				
		1 X 10 - <20%	Referent				
		1 X ≥ 10%	Referent				
		2 X 0 - <5%	Referent				
		2 X 5 - <10%	0.11	0.10	1.11	0.92	1.34
		2 X 10 - <20%	-0.14	0.10	0.87	0.72	1.05
		2 X ≥ 20%	-0.23	0.11	0.79	0.64	0.98
		3 X 0 - <5%	Referent				
		3 X 5 - <10%	0.24	0.11	1.27	1.02	1.56
		3 X 10 - <20%	-0.02	0.11	0.98	0.79	1.22
		3 X ≥ 20%	-0.24	0.12	0.79	0.62	0.99
		4 X 0 - <5%	Referent				
		4 X 5 - <10%	-0.02	0.11	0.98	0.79	1.23
		4 X 10 - <20%	-0.16	0.12	0.85	0.67	1.07
		4 X ≥ 20%	-0.48	0.14	0.62	0.47	0.81

5 X 0 - <5%	Referent					
5 X 5 - <10%	0.10	0.09	1.10	0.92	1.33
5 X 10 - <20%	-0.13	0.11	0.88	0.71	1.08
5 X ≥ 20%	-0.50	0.12	0.61	0.48	0.77
6 X 0 - <5%	Referent				
6 X 5 - <10%	-0.08	0.11	0.92	0.74	1.15
6 X 10 - <20%	-0.27	0.15	0.76	0.57	1.02
6 X ≥ 20%	-0.64	0.33	0.53	0.27	1.02
7 X 0 - <5%	Referent				
7 X 5 - <10%	-0.24	0.36	0.79	0.39	1.60
7 X 10 - <20%	N/A [b]				
7 X ≥ 20%	N/A [b]				

Gender[c]	0.0852
Risk code[c]	<0.0001
Time[c]	<0.0001
Feedlot[c]	<0.0001

[a]Model was estimated using a generalized estimating equation with cohort as a panel variable and a exchangeable correlation structure

[b]The interaction between temporal pattern and cumulative morbidity could not be computed because there were no cohorts with these covariate patterns

[c]Estimates for temporal pattern and its interactions were adjusted for gender, time, and feedlot (coefficients not shown, but are available from the authors on request)

Table 3.8 Final multivariable logistic regression model[a] of cumulative retreatment risk within feedlot cattle cohorts (n = 7,447)

Covariate	$P > \chi^2$	Level	b	Robust S.E. (b)	OR	95% CI OR	
Intercept			-1.17	0.20			
Temporal pattern	0.6256	1	Referent				
		2	-0.10	0.19	0.91	0.62	1.31
		3	-0.30	0.29	0.74	0.42	1.30
		4	-0.50	0.29	0.61	0.34	1.07
		5	-0.33	0.27	0.72	0.42	1.24
		6	-0.30	0.38	0.74	0.35	1.57
		7	-0.36	0.59	0.70	0.22	2.23
Arrival weight (kg)	0.2690	≥ 409	Referent				
		363-408	0.01	0.15	1.01	0.75	1.35
		318-362	0.03	0.13	1.03	0.81	1.32
		272-317	0.03	0.12	1.03	0.81	1.31
		227-271	-0.12	0.13	0.88	0.68	1.15
		182-226	-0.13	0.15	0.88	0.66	1.18
		<182	-0.46	0.28	0.63	0.36	1.09
Cumulative morbidity	<0.0001	0 - <5%	Referent				
		5 - <10%	0.22	0.10	1.24	1.03	1.50
		10 - <20%	0.43	0.09	1.53	1.28	1.83
		$\geq 20\%$	0.66	0.09	1.94	1.62	2.34
Temporal pattern X Arrival weight	0.0031	1 X ≥ 409	Referent				
		1 X 363-408	Referent				
		1 X 318-362	Referent				
		1 X 272-317	Referent				
		1 X 227-271	Referent				
		1 X 182-226	Referent				
		1 X <182	Referent				
		2 X ≥ 409	Referent				
		2 X 363-408	0.11	0.21	1.12	0.75	1.69
		2 X 318-362	0.19	0.18	1.21	0.85	1.72
		2 X 272-317	0.21	0.18	1.23	0.87	1.75
		2 X 227-271	0.38	0.19	1.46	1.01	2.12
		2 X 182-226	0.49	0.20	1.64	1.11	2.42
		2 X <182	0.78	0.33	2.17	1.14	4.15
		3 X ≥ 409	Referent				
		3 X 363-408	0.58	0.30	1.79	0.98	3.25
		3 X 318-362	0.42	0.28	1.53	0.87	2.66
		3 X 272-317	0.61	0.29	1.85	1.06	3.23
		3 X 227-271	0.79	0.29	2.20	1.24	3.92
		3 X 182-226	0.86	0.30	2.36	1.30	4.26
		3 X <182	1.30	0.43	3.66	1.57	8.55

		4 X ≥ 409	Referent				
		4 X 363-408	0.54	0.31	1.72	0.94	3.16
		4 X 318-362	0.70	0.29	2.01	1.15	3.53
		4 X 272-317	0.77	0.29	2.15	1.22	3.79
		4 X 227-271	0.91	0.30	2.50	1.39	4.49
		4 X 182-226	0.72	0.31	2.05	1.11	3.78
		4 X <182	1.24	0.44	3.45	1.45	8.20
		5 X ≥ 409	Referent				
		5 X 363-408	0.47	0.29	1.59	0.91	2.80
		5 X 318-362	0.45	0.27	1.56	0.92	2.67
		5 X 272-317	0.45	0.28	1.56	0.91	2.68
		5 X 227-271	0.60	0.28	1.81	1.04	3.17
		5 X 182-226	0.77	0.30	2.16	1.20	3.89
		5 X <182	0.77	0.48	2.15	0.84	5.53
		6 X ≥ 409	Referent				
		6 X 363-408	0.67	0.40	1.96	0.90	4.25
		6 X 318-362	0.55	0.38	1.73	0.82	3.65
		6 X 272-317	0.39	0.39	1.48	0.69	3.16
		6 X 227-271	0.66	0.40	1.93	0.89	4.21
		6 X 182-226	0.63	0.43	1.88	0.82	4.35
		6 X <182	0.76	0.63	2.14	0.62	7.35
		7 X ≥ 409	Referent				
		7 X 363-408	1.01	0.62	2.75	0.81	9.29
		7 X 318-362	0.36	0.62	1.44	0.43	4.81
		7 X 272-317	0.40	0.64	1.49	0.43	5.22
		7 X 227-271	0.16	0.65	1.17	0.33	4.18
		7 X 182-226	0.11	0.70	1.12	0.28	4.39
		7 X <182	-0.21	0.82	0.81	0.16	4.09
Temporal pattern X Cumulative morbidity	0.0006	1 X 0 - <5%	Referent				
		1 X 5 - <10%	Referent				
		1 X 10 - <20%	Referent				
		1 X ≥ 10%	Referent				
		2 X 0 - <5%	Referent				
		2 X 5 - <10%	-0.05	0.12	0.95	0.74	1.21
		2 X 10 - <20%	0.06	0.12	1.06	0.84	1.33
		2 X ≥ 20%	-0.09	0.12	0.91	0.72	1.16
		3 X 0 - <5%	Referent				
		3 X 5-10%	-0.03	0.13	0.97	0.75	1.25
		3 X 10 - <20%	0.03	0.13	1.03	0.80	1.33
		3 X ≥ 20%	-0.28	0.13	0.75	0.59	0.97
		4 X 0 - <5%	Referent				
		4 X 5-10%	-0.11	0.14	0.90	0.68	1.19
		4 X 10 - <20%	-0.31	0.14	0.73	0.56	0.96
		4 X ≥ 20%	-0.19	0.15	0.83	0.61	1.11

5 X 0 - <5%	Referent					
5 X 5-10%	-0.12	0.12	0.89	0.70	1.12
5 X 10 - <20%	-0.06	0.12	0.94	0.74	1.19
5 X ≥ 20%	-0.30	0.13	0.74	0.57	0.96
6 X 0 - <5%	Referent					
6 X 5-10%	-0.41	0.14	0.66	0.50	0.88
6 X 10 - <20%	-0.38	0.18	0.69	0.48	0.98
6 X ≥ 20%	-0.44	0.21	0.65	0.43	0.97
7 X 0 <5%	Referent					
7 X 5 - <10%	-1.42	0.56	0.24	0.08	0.72
7 X 10 - <20%	N/A[b]					
7 X ≥ 20%	N/A[b]					

Gender[c]	0.0745
Risk code[c]	<0.0001
Time[c]	<0.0001
Feedlot[c]	<0.0001

[a]Model was estimated using a generalized estimating equation with cohort as a panel variable and a exchangeable correlation structure

[b]The interaction between temporal pattern and cumulative morbidity could not be computed because there were no cohorts with these covariate patterns

[c]Estimates for temporal pattern and its interactions were adjusted for gender, risk code, time, and feedlot (coefficients not shown, but are available from the authors on request)

Figure 3.1 Height values (a function of error sum of squares)[a] resulting from use of Ward's hierarchical clustering method (reduction in the number of clusters moving right to left) to determine clusters of temporal patterns of bovine respiratory disease complex (BRDC) cases among feedlot cattle cohorts.
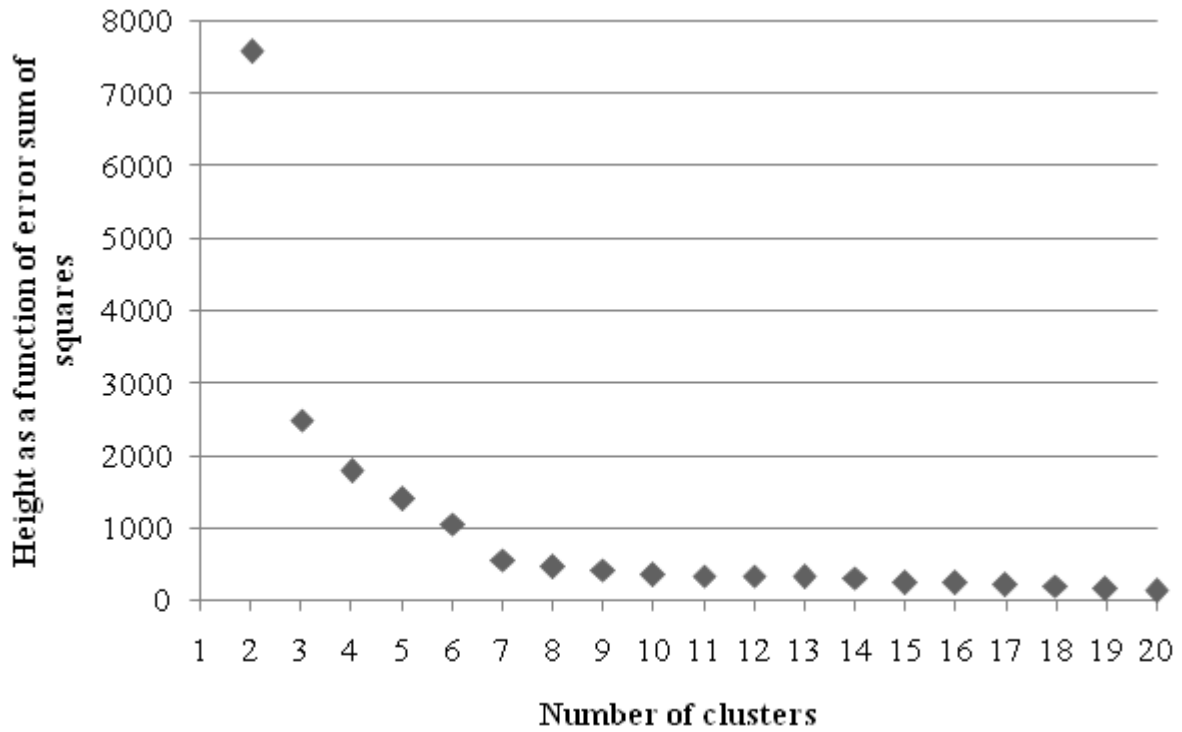

[a]Output from the HCLUST function in R for Ward's hierarchical clustering method

1   **Figure 3.2 Smoothed curves[a] representing temporal patterns (cumulative percent) of bovine respiratory disease complex**

2   **(BRDC) cases occurring within cohorts of feedlot cattle during the first 100 days at risk (variability bands, representing two**

3   **standard errors from the estimate are represented by dashed lines)**
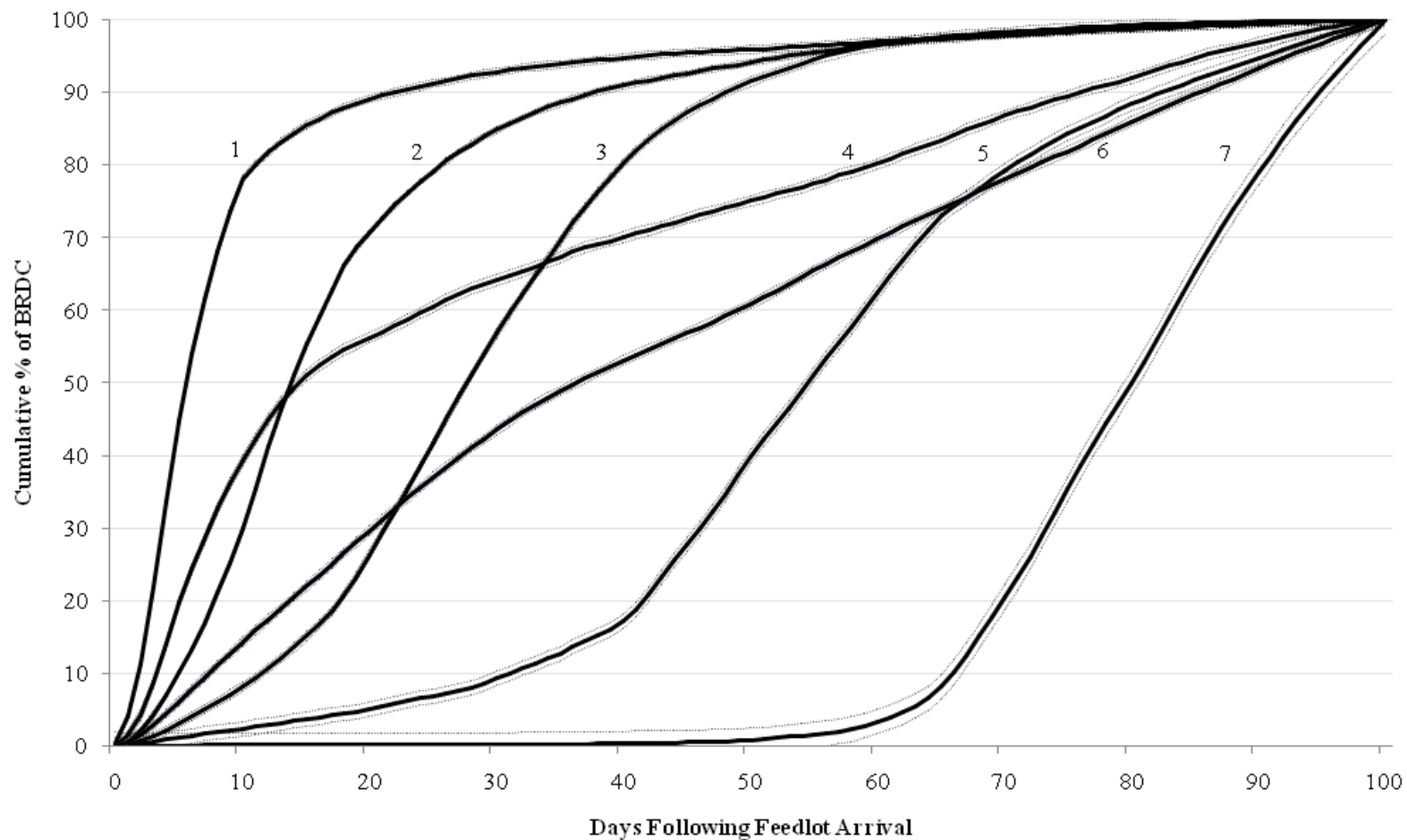

5

6   [a] Ward's hierarchical clustering method was used to group cohorts with similar distributions of the cumulative daily percentage of cases.

Figure 3.3 Model predicted[a] mean daily weight gain (kg/animal/day) for feedlot cattle cohorts by temporal pattern and feedlot-assigned respiratory risk code (light grey = low risk, dark grey = high risk). Error bars represent 95% confidence intervals.
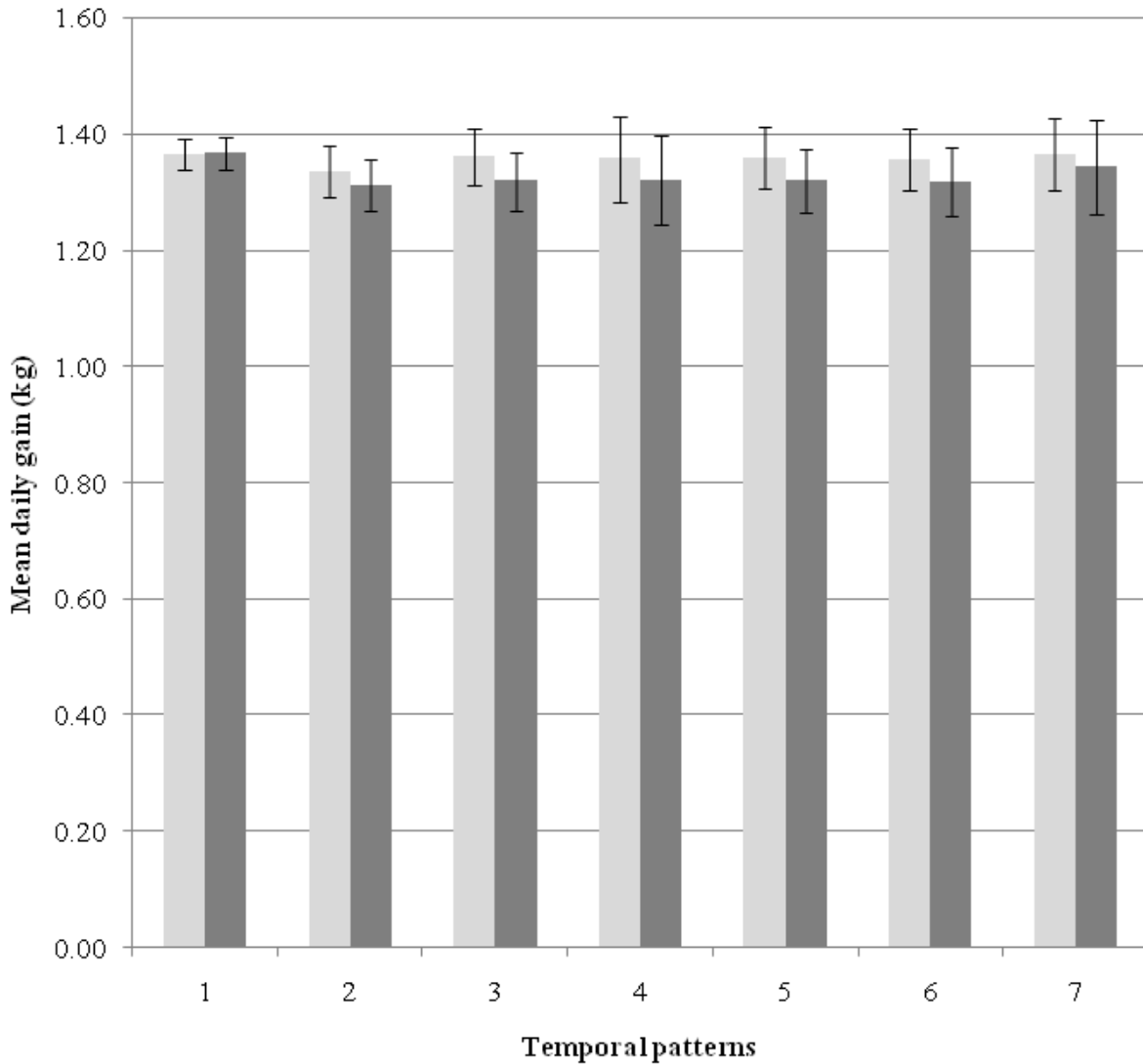

[a]Estimates from a linear mixed model, where effects for arrival weight, gender, cumulative morbidity, interaction of temporal pattern and arrival weight, and time were included as weighted averages with the number of observations within each covariate group multiplied by the corresponding coefficient.

Figure 3.4 Model predicted[a] mean days on feed for feedlot cattle cohorts by temporal pattern of respiratory disease and arrival weight category. Bars represent temporal patterns within weight categories (Temporal Pattern One to Seven moving left to right). Error bars represent 95% confidence intervals.
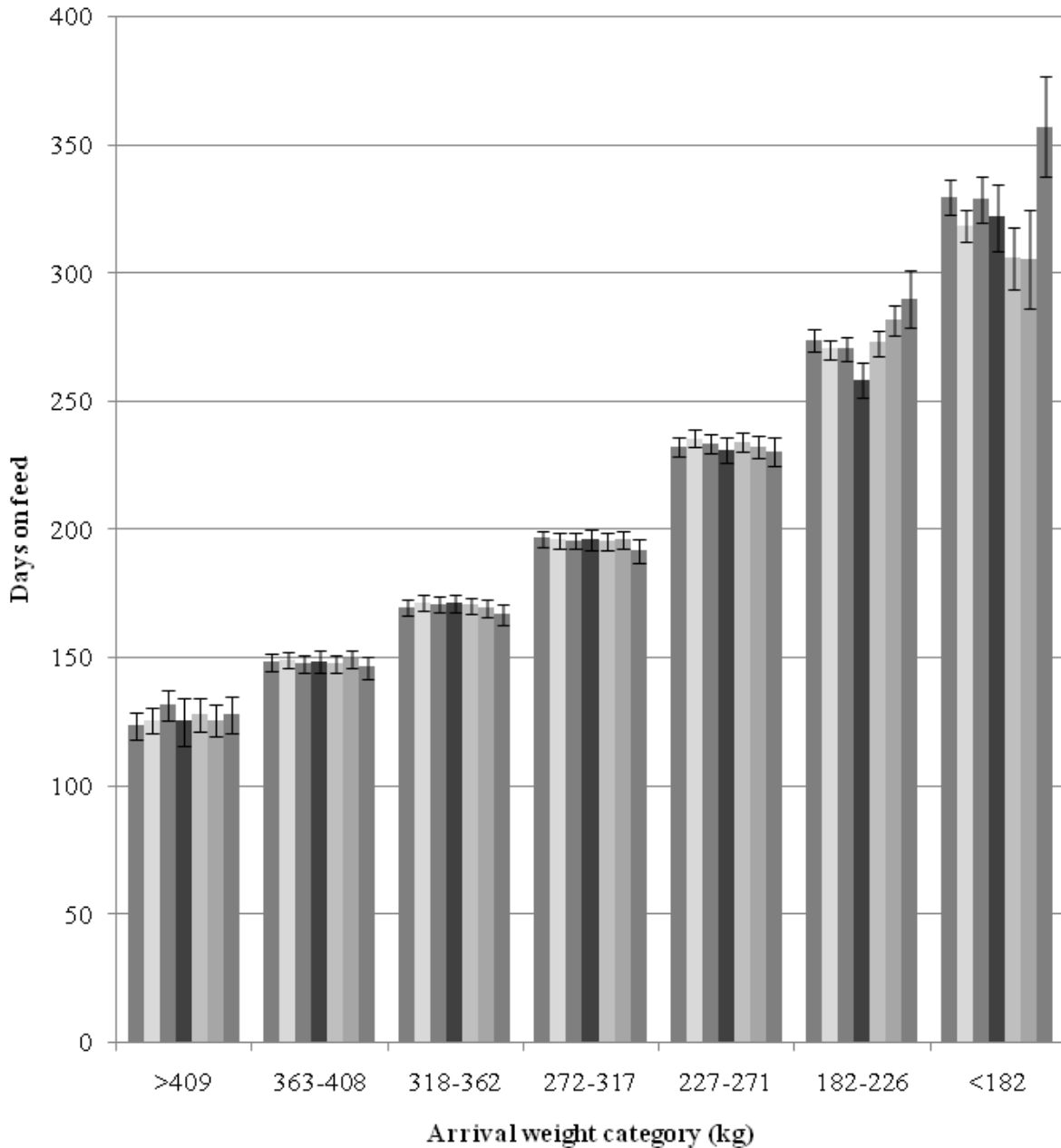
[a]Estimates from a linear mixed model, where effects for gender, cumulative morbidity, risk code, interaction of temporal pattern and risk code, and time were included as weighted averages with the number of observations within each covariate group multiplied by the corresponding coefficient.

Figure 3.5 Model predicted[a] mean carcass weight per animal within feedlot cattle cohorts by temporal pattern of respiratory disease and arrival weight category. Bars represent temporal patterns within weight categories (Temporal Pattern One to Seven moving left to right). Error bars represent 95% confidence intervals.
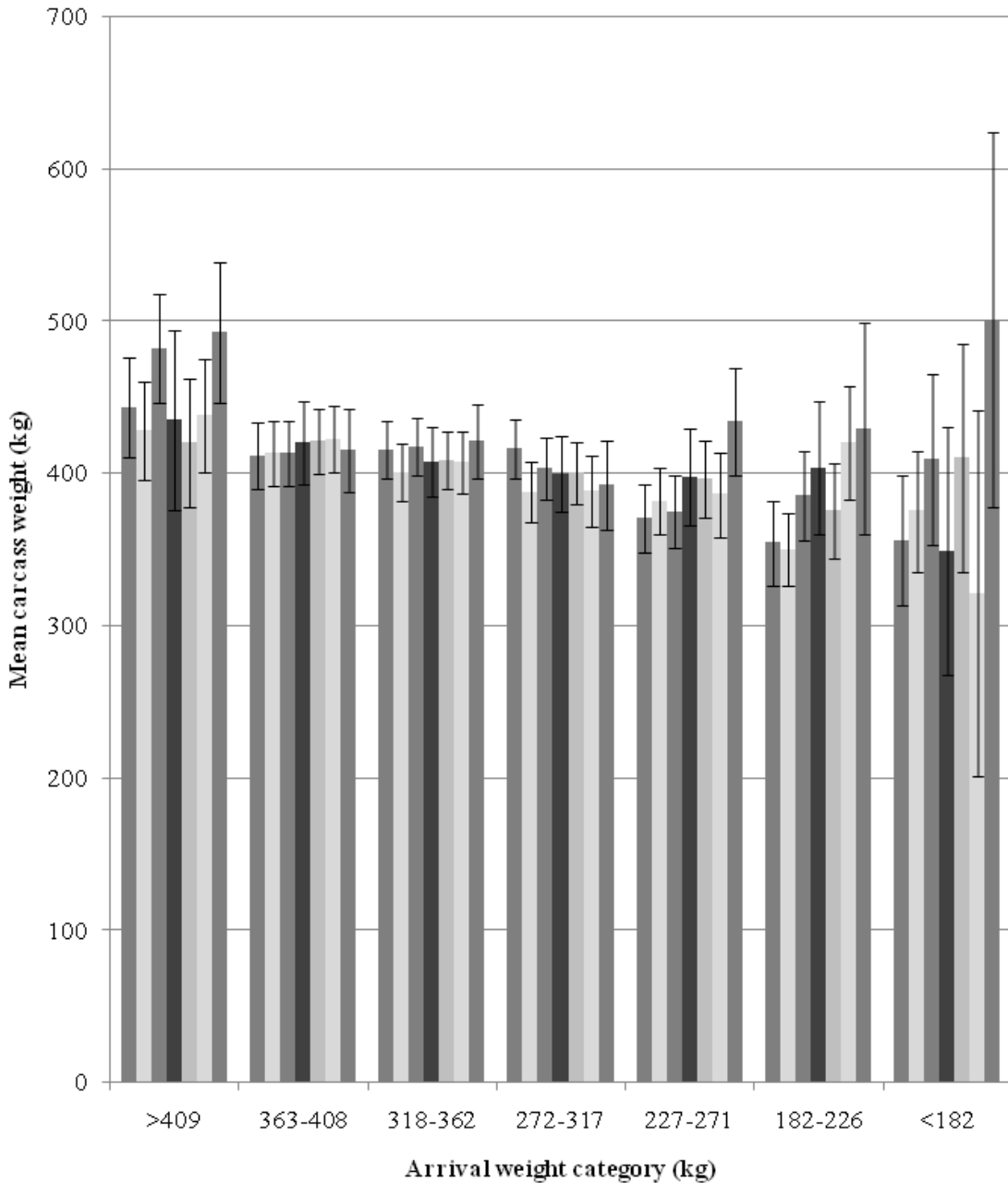

[a]Estimates from a linear mixed model, where effects for gender, cumulative morbidity, risk code, interaction of temporal pattern and risk code, and time were included as weighted averages with the number of observations within each covariate group multiplied by the corresponding coefficient.

Figure 3.6 Model predicted[a] percentage of Yield Grade One and Two carcasses within feedlot cattle cohorts by temporal pattern of respiratory disease and gender (light grey = male, dark grey = female). Error bars represent 95% confidence intervals.
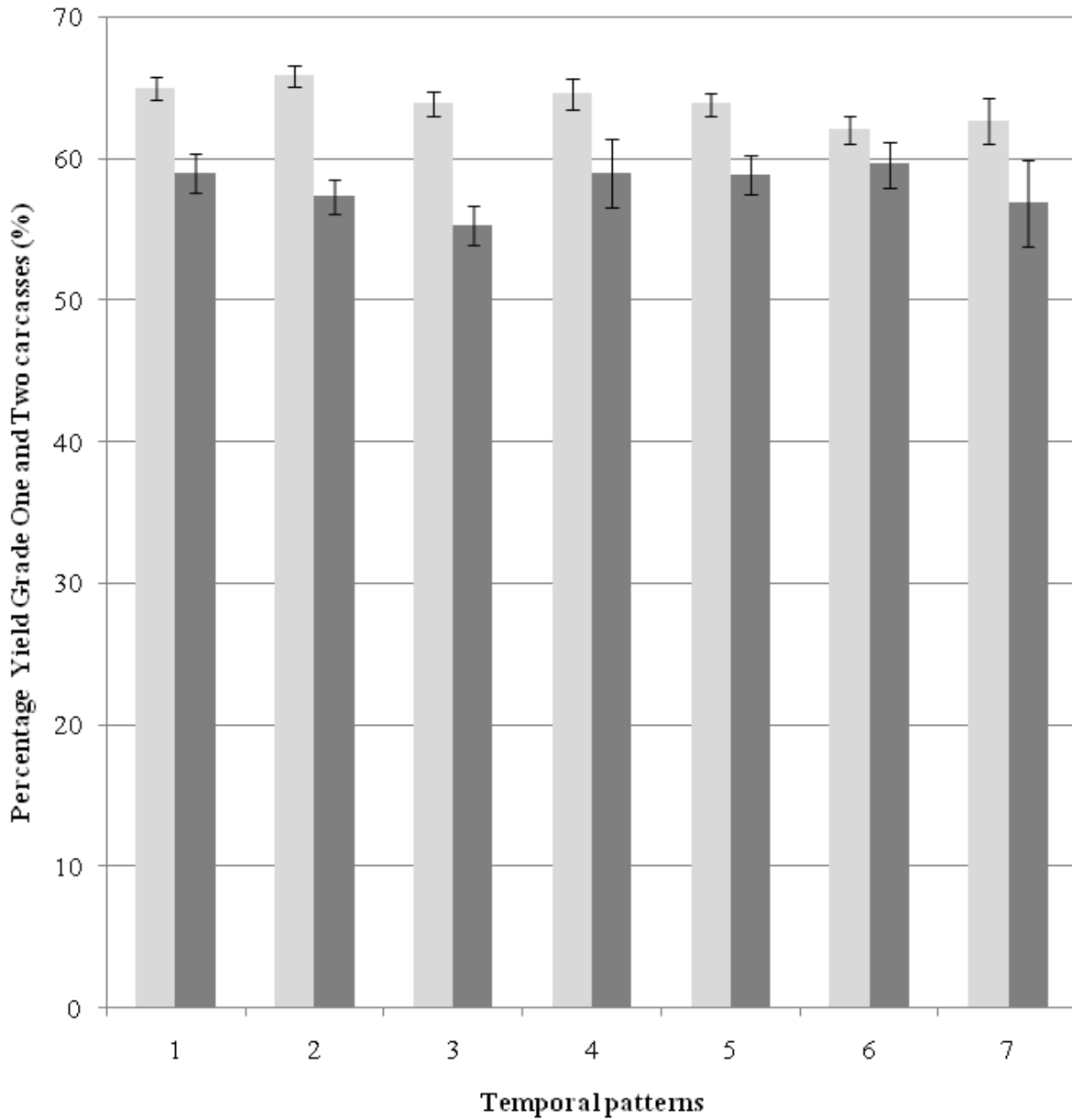
[a]Estimates from a multivariable GEE logistic regression model, where effects for arrival weight, risk code, cumulative morbidity, time, and feedlot were included as weighted averages with the number of observations within each covariate group multiplied by the corresponding coefficient.

Figure 3.7 Model predicted[a] percentage Choice and Prime carcasses within feedlot cattle cohorts by temporal pattern of respiratory disease and arrival weight category (kg). Bars represent temporal patterns within weight categories (Temporal Pattern One to Seven moving left to right). Error bars represent 95% confidence intervals.
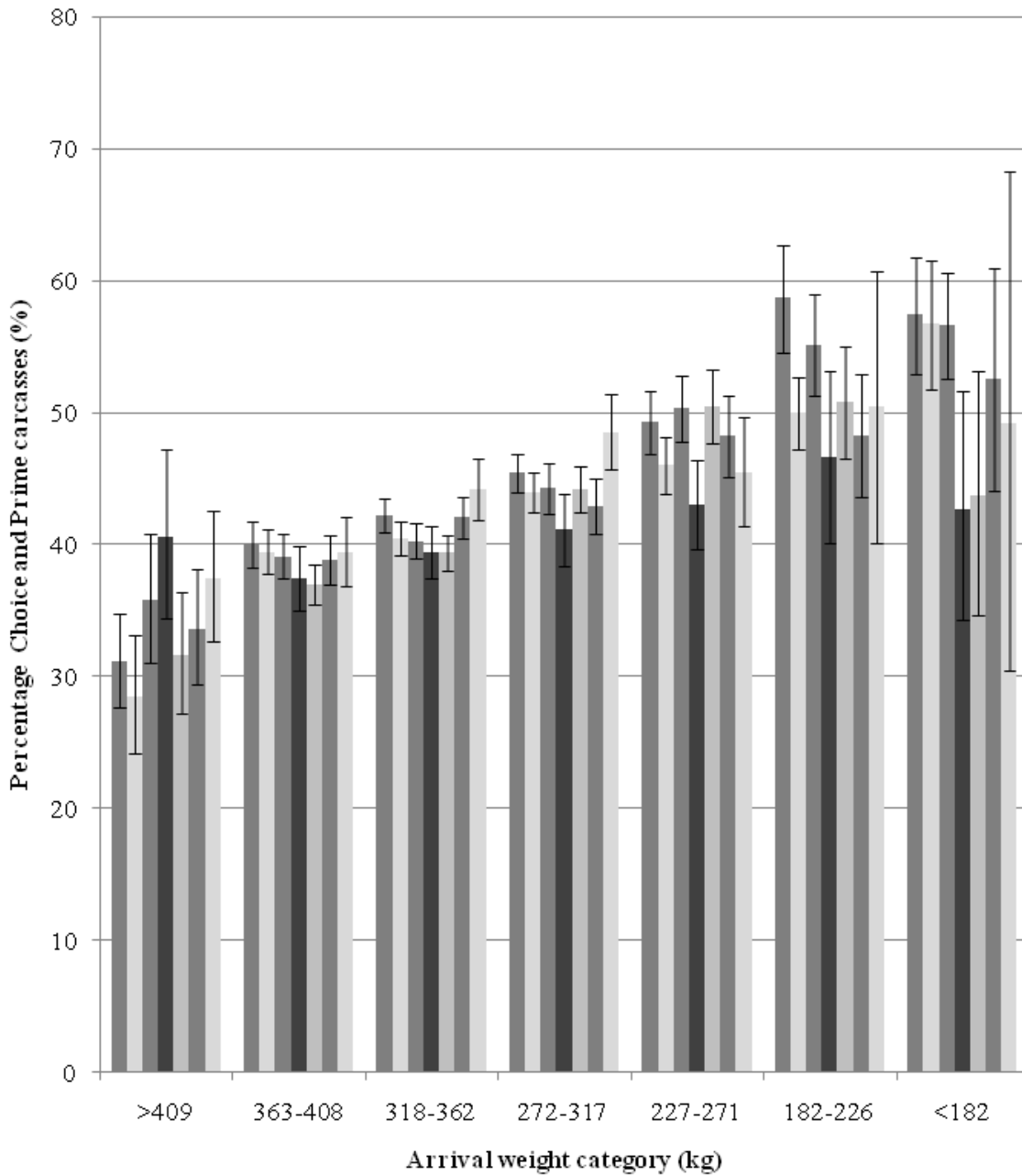

[a]Estimates from a multivariable GEE logistic model, where effects for gender, risk code, cumulative morbidity, time, feedlot, and interaction of temporal pattern and cumulative morbidity were included as weighted averages with the number of observations within each covariate group multiplied by the corresponding coefficient.

Figure 3.8 Model predicted[a] cumulative mortality risk within feedlot cattle cohorts by temporal pattern of respiratory disease and arrival weight category. Bars represent temporal patterns within weight categories (Temporal Patterns One to Seven moving left to right). Error bars represent 95% confidence intervals.

[a]Estimates from a multivariable GEE logistic model, where effects for gender, risk code, cumulative morbidity, time, feedlot, the interaction of temporal pattern and cumulative morbidity, and the interaction of temporal pattern and risk code were included as weighted averages with the number of observations within each covariate group multiplied by the corresponding coefficient.

Figure 3.9 Model predicted[a] cumulative retreatment risk within feedlot cattle cohorts by temporal pattern of respiratory disease and arrival weight category. Bars represent temporal patterns within weight categories (Temporal Patterns One to Seven moving left to right). Error bars represent 95% confidence intervals.


[a]Estimates from a multivariable GEE logistic model, where effects for gender, risk code, cumulative morbidity, time, feedlot, the interaction of temporal pattern and cumulative morbidity, and the interaction of temporal pattern and risk code were included as weighted averages with the number of observations within each covariate group multiplied by the corresponding coefficient.

CHAPTER 4 - Quantifying the effects of common risk factors for combined mortality and culling risk in feedlot cattle populations using a mixed effects count model

A.H. Babcock[a,b], D.G. Renter[a,*], B.J. White[b], S.R. Dubnicka[c], D.U. Thomson[b], S.E. Ives[d],

H.M. Scott[a]

[a]Department of Diagnostic Medicine and Pathobiology, College of Veterinary Medicine, Kansas State University, Manhattan, Kansas, United States

[b]Department of Clinical Sciences, College of Veterinary Medicine, Kansas State University, Manhattan, Kansas, United States

[c]Department of Statistics, College of Arts and Sciences, Kansas State University, Manhattan, Kansas, United States

[d]Cactus Operating, LLC., Cactus, Texas, United States

Abstract

Mortality and culling of cattle has a substantial economic impact on the feedlot industry. Since criteria for culling may vary and also may affect cumulative mortality, it is important to assess combined mortality and culling risk when evaluating cattle losses over time and among feedlots. There are no published multivariable assessments of risk factors associated with combined mortality and culling risk. Our objective was to evaluate mortality and culling risk in commercial feedlot cattle and quantify the effects of common risk factors (arrival weight, gender, and arrival month) using data routinely collected by commercial feedlots. We used retrospective cumulative cohort-level health data representing 8,904,965 animals in 54,416 cohorts from 16 U.S. feedlots (2000 – 2007). We quantified the effects of potential risk factors utilizing different functional forms of count models (Poisson, negative binomial, generalized negative binomial, and mixed negative binomial). Model fit comparisons were made utilizing

likelihood ratio tests, Bayesian information criteria, standardized deviance residuals, and observed-minus-predicted probabilities. Following model assessment, we determined that the mixed negative binomial with a random effect for arrival year and feedlot fit the data best. All of the independent variables (arrival weight, gender, arrival month) and all corresponding first order interaction terms were statistically ($P < 0.05$) associated with combined mortality and culling risk. Results showed that as arrival weight increased, mortality and culling risk tended to decrease, but the effect of arrival weight was modified both by gender and arrival month. Combined mortality and culling risk appeared to increase from 2000 through 2003, decrease in 2004, and then remain relatively constant through 2007. There also was evidence of seasonality in combined mortality and culling risk for both males and females, with a higher risk for cattle arriving at the feedlot in summer, fall, and winter months (June through January) when compared with cattle arriving in February through May. Female cohorts arriving in August - October had disproportionately higher mortality and culling risks compared to males arriving in those months. Our results quantify effects of covariate patterns that have been heretofore difficult to fully evaluate in earlier smaller scale studies; in addition, they illustrate the importance of utilizing multivariable approaches when quantifying risk factors in heterogeneous feedlot populations. Estimated effects from our model and other similar models may be useful for cattle risk managers attempting to manage financial risks associated with adverse health events based on data that are commonly available.

Keywords: Cattle; mortality; risk factors; negative binomial regression

Introduction

Losses due to cattle mortality and culling have tremendous economic impacts on North American feedlot production systems (Smith et al., 2001). Economic losses include costs associated with feed consumption, personnel labor, pharmaceutical products, carcass disposal, and loss of interest on invested money, as well as price paid for the animal. Despite continued advances in health management programs and pharmaceutical products, recent research indicates that U.S. feedlot mortality risk has increased over time (Loneragan et al., 2001; Loneragan, 2004; Babcock et al., 2006). The apparent increased risk over time may be due to true increases in mortality across feedlot populations, changes in cattle demographics and corresponding risk factors, or an increasing reluctance of feedlots to cull cattle. Culling is defined as removal of

animals from their cohort prior to harvest. Feedlots may have different criteria on culling chronically ill or poor performing animals prior to harvest, and may cull animals in an attempt to decrease overall mortality. If feedlot personnel cull animals quickly and aggressively, the mortality risk for the population may appear low relative to similar populations of cattle in feedlots with more conservative culling practices. Some researchers have suggested that a more comprehensive approach to assessing cattle losses across multiple feedlots and years would require that data on mortality and culling are combined and assessed simultaneously using multivariable models accounting for potential differences in cattle populations (Loneragan, 2004).

Multivariable approaches assessing risk factors for mortality and culling are important because cattle demographics changing over time, within and across feedlots, can confound the observed relationship between seasonal patterns and health risks (Ribble et al., 1995). Literature quantifying effects of risk factors of feedlot mortality are limited and there are no published data on factors affecting culling of feedlot cattle. Arrival weight, gender, arrival month, weather, and commingling of cattle have been found to be associated with feedlot mortality risk (Martin et al., 1982; MacVean et al., 1986; Ribble et al., 1998; Loneragan, 2004). However, most studies of mortality risks have used data from only a limited number of feedlots, or else used data aggregated by month at the feedlot level; on the other hand, feedlots tend to purchase, manage and market cattle as cohorts (often called "lots" of cattle). There are no published data demonstrating the effects of multiple risk factors and their interactions on combined mortality and culling risk in cohorts of commercial feedlot cattle. Quantifying the effects of potential risk factors would allow managers of feedlot finances and cattle health to make more informed production decisions about cattle cohorts that they typically purchase, and also provide data on atypical cohorts where the effects of risk factors may be difficult to quantify due to a lack of data. The objective of our study was to quantify the effects of common potential risk factors (i.e., arrival weight, gender, and arrival month) on combined cumulative mortality and culling risk within cattle cohorts using data that are routinely collected by commercial feedlots.

Materials and methods

Data

We collected and verified cohort-level data representing groups of cattle that had previously arrived at 23 feedlots in four U.S. states (Colorado, Kansas, Nebraska, and Texas) from 1989 – 2008. Cohorts were equivalent to a "lot" of animals that may or may not have been housed in the same physical location (pen) for the duration of the feeding period; however, all animals in a lot were purchased, managed and marketed similarly. Cohort-level variables consistently collected across feedlots were: mean weight on arrival at the feedlot, gender, arrival month, and arrival year. Arrival weight was recorded on an interval scale as the mean weight of cattle in each cohort. Gender (consistent within lot), arrival month, and arrival year were all recorded on a nominal scale. Cattle were designated as male or female in our analysis, rather than steer or heifer, as data on the castration or pregnancy status on arrival to the feedlot were not available for all cohorts. Data on several other potential risk factors were not collected consistently across all feedlots; therefore, additional variables (e.g. shipping distance, source location, preconditioning) were not used in the analysis. Our study population was selected based on requirements that: feedlots reported cohort-level data on both mortality and culling, cohorts arrived to the feedlot between 2000 and 2007, cohorts were classified as male or female (not mixed), cohorts contained between 40 to 340 animals when they arrived at the feedlot, and cohorts had a mean arrival weight between 91 and 470 kg. A total of 54,416 cohorts from 16 feedlots met our inclusion criteria. The sum of mortality and culling counts for each cohort (given the number of cattle at risk) was used to generate the outcome of interest; hereafter referred to as the combined mortality and culling risk, representing the cumulative incidence over each cohort's feeding period.

Descriptive statistics

Descriptive statistics were computed for all variables in the dataset. For interval scale variables, minima, maxima, and quartiles were computed. Frequency tables were generated for ordinal and nominal variables.

Prior to modeling building the NBVARGR procedure of Stata version 10 (Stata Corp, College Station, TX, USA) was used to plot probabilities for within-cohort counts of mortality and culling based on the observed data and against each of Poisson and negative binomial distributions.

Regression model building

Model building for the study was split into three major stages: 1) bivariable analyses assessing the association of the combined mortality and culling risk and each independent variable (performed first using negative binomial regression (NBR), then a multivariable NBR model; at each stage of model building a likelihood ratio test was performed comparing the NBR model to a Poisson model (PRM); 2) comparison of a NBR model to the generalized NBR (GNBR); and 3) implementation of a NBR mixed model (MNBR). For all analyses, the total number of cattle within each cohort on arrival to the feedlot was specified as the exposure variable while the count of combined mortality and culling within each cohort was the outcome of interest.

Negative binomial and Poisson regression

For the bivariable portion of the analysis the NBREG procedure of Stata version 10 was utilized. The use of NBR in the initial stages of model building allowed for the comparison of NBR to PRM by using a likelihood ratio test ($P < 0.05$). Mean arrival weight was the only independent variable recorded on a continuous scale; however, it did not meet linear assumptions. Arrival weight was therefore broken into 22.7 kg categories coded using Walter's hierarchical methods (Walter, 1987). Backward selection, utilizing an elimination procedure, was used to collapse arrival weight categories inward toward the initially centered referent category (295 – 317 kg: this category corresponded to the most frequent feedlot arrival weight). This process resulted in nine weight categories and a new referent category spanning 272 – 317 kg. Arrival month, year, and gender were analyzed on nominal scale as initially recorded by feedlots. Feedlot itself was also considered as an independent categorical effect in the bivariable portion of model building; later, it was treated as a random effect in multivariable models.

Significance testing for all stages of model building was performed using a likelihood-ratio test comparing the full model to the reduced model (Dohoo et al., 2003). Main effect multivariable models were fit using manual backward selection (using $P < 0.05$ to remain in the model) with covariates that were associated ($P < 0.1$) with the outcome in the bivariable models. Two-way interactions among arrival weight, gender, and arrival month were fit subsequent to the main effect model using manual backward selection ($P < 0.05$). Two-way interactions involving

arrival year and feedlot were not assessed as these were considered random variables and were later included as random effects in the third stage of the model building process.

Influential observations were assessed by constructing the full multivariable model using the GLM command in Stata version 10 with a log link and "nbinomial" family specification. In addition, the shape parameter (alpha) derived from the full NBR model utilizing the NBREG command was used, resulting in the same beta coefficients and standard errors for all parameters. Subsequent to fitting the final multivariable model with GLM, values for Cook's distance were obtained, as these values could not be generated with the NBREG command.

Generalized negative binomial regression

The GNBREG command (Stata, version 10) was used to fit a generalized negative binomial regression (GNBR); that is, a generalization of the NBR where the shape parameter (alpha) is parameterized in an attempt to better explain any overdispersion in the data. Main effects and two-way interactions for the main model were selected as described previously. Independent variables for the shape parameter were specified first in a bivariable approach. Each main effect for the shape parameter was fit individually, and statistical significance was determined by *a* Wald χ^2 test ($P < 0.1$). Observed minus predicted probabilities, standardized deviance residuals, and Bayesian information criteria (BIC) (hereafter referred to as "model diagnostics") were then compared among GNBR models. While considering model diagnostics, *variables deemed significant based on* Wald χ^2 test *from* the bivariable portion of the shape parameter assessment were then fit utilizing manual backward selection ($P < 0.05$). Model diagnostics for the final GNBR were compared to NBR and PRM fit previously to assess quality of fit, and determine which functional form was most appropriate for the final model.

Negative binomial mixed model

After determining that an NBR model was appropriate for these data, a negative binomial mixed model (MNBR) was assessed (XTNBREG, Stata version 10). This procedure allows one panel variable for random effects, which we used to account for lack of independence among cattle cohorts within arrival years and feedlots. To account for both year (n = 8) and feedlot (n= 11 in 2000, 13 in 2001-02, 14 in 2003, and 16 in 2004-07) concurrently, the two were combined and included as a single panel variable with 115 categories. Thereafter, predictor variables were fit using the same manual backward selection method as described above. A likelihood ratio test

then was performed to test the panel estimator compared to a pooled estimator of the NBR model, thus giving a formal statistical test comparing model fit between the MNBR and NBR (Stata, 2007).

Results

Descriptive statistics

The analyzed dataset consisted of 54,416 cohorts (representing 8,904,965 individual animals) from 16 different feedlots during arrival years 2000 – 2007. The participating feedlots were located in Colorado, Kansas, Nebraska, and Texas, and their one-time capacities ranged from 22,000 to 82,000 cattle. The number of cattle within cohorts ranged from 40 to 340, with a median of 150 and mean of 163 animals (SE = 0.32). Of the cohorts, 64% were classified as males and 36% as females. Cohort-level mean cattle arrival weight ranged from 119 to 468 kg, with a median of 322 kg and mean of 316 kg (SE = 0.52). Cumulative mortality risk ranged from 0% to 31.9% with a median of 0.9% and mean of 1.5% (SE = 0.009%). Culling risk ranged from 0% to 100%, with a median of 0.9% and a mean of 0.7% (SE = 0.009%). The mean ratio of mortalities to culls across feedlots (all years) ranged from 1.3 to 5.1, with a median of 2.0 and a mean of 2.3 (SE = 0.004), and among different years (all feedlots) ranged from 1.2 to 3.2 with a median of 2.0 and mean of 2.1 (SE = 0.003). The combined mortality and culling risk ranged from 0% to 100%, with a median of 1.4% and mean of 2.3% (SE = 0.43%). The distribution of combined mortality and culling counts within cattle cohorts is displayed in Figure 4.1.

Model selection (Poisson, negative binomial, and generalized negative binomial regression)

Plots of the observed probability of counts in the dataset compared to the expected probabilities based on Poisson and negative binomial distributions indicated that the negative binomial distribution was a better fit than the Poisson distribution (Figure 4.2). In the final NBR model, all main effects and two-way interactions evaluated were statistically significant (results not shown). The likelihood-ratio test examining the null hypothesis that the dispersion parameter (alpha) was equal to zero was highly significant (alpha = 0.558 and $\chi^2(1) = 5.6e+04$, $P < 0.001$), indicating that the count of combined mortalities and culls were overdispersed, and the observed data were better modeled utilizing NBR.

For GNBR, likelihood ratio tests and model diagnostics indicated that that the shape parameter of the GNBR was best specified using feedlot, arrival year, arrival month, arrival weight, and gender. Observed minus predicted probabilities were very similar between the NBR model and GNBR model (Figure 4.3). The PRM model had a greater number (327) of deviance residuals $|d_i| > 4$ compared to the NBR or GNBR (10 and 6 respectively). While large residuals can reflect errors in the dataset, these outliers were left in the analysis because all were biologically plausible observations and none were deemed to be influential by Cooks distance. For the NBR model and GNBR models, only 0.6% of the deviance residuals were $> |2|$; indicating relatively good model fit (Liu et al., 2005).

Based on observed minus predicted probabilities (Figure 4.3), deviance residuals, and BIC there was no apparent benefit to specifying the alpha parameter using the GNBREG (Stata, version 10) procedure. Therefore, the simpler NBR model was preferred to the generalized model. Once it was determined that NBR was the preferred model, a MNBR was then utilized. The likelihood ratio test comparing the panel estimator to the pooled estimator (NBR) was significant ($\chi^2(1) = 3845.27$, $P < 0.001$) indicating that the MNBR model was preferred to the NBR model (Stata, 2007).

Model results (negative binomial and generalized negative binomial regression)

To assess the pattern of combined mortality and culling risk over time while holding all covariates at mean values, model-adjusted (marginal) mean mortality and culling risks across arrival months and years were plotted based on results from the final NBR model (Figure 4.4 and Figure 4.5). Combined mortality and culling risk appeared to be seasonal, and there were apparent differences in risk across arrival years. Combined mortality and culling risk increased from 2000 through 2003, and then appeared to decrease in 2004 and stayed relatively stable across 2005 – 2007 (Figure 4.5).

In the bivariable MNBR models, all variables investigated were significantly associated with risk. The final multivariable model also included all independent variables evaluated and indicated that gender, arrival month, and arrival weight all significantly modified the effect of each another (Table 1). The random effect for arrival year and feedlot was also statistically significant in the final model (Table 1; $P < 0.01$).

In general, as arrival weight increased combined mortality and culling risk decreased (Figure 4.6); further, across the very light (< 182 kg) and middleweight classes (205 – 227 through 250 – 271 kg) males and females had very similar estimates of risk. For the 182 – 204, 205 – 227, and > 362 kg weight classes, female cohorts displayed higher risk as compared to males. In contrast, combined mortality and culling risk appeared to be higher for males compared to female cohorts in the 272 – 317 kg and 341 – 362 kg weight categories (Figure 4.6).

There appeared to be a seasonal pattern to the combined mortality and culling risk for both male and female cohorts, with a higher risk for cattle arriving at the feedlot in summer, fall, and winter months (June through January) than for cattle arriving in February through May (Figure 4.7). Female cohorts arriving in August, September, and October displayed higher risks compared to male cohorts arriving at the feedlot during those months (Figure 4.7).

Although lighter cattle tended to have higher combined mortality and culling risk when compared to heavier cattle, there were several differences among the weight categories within each month, and within weight categories across several months (Figure 4.8). For cattle arriving during May through October, weight categories < 182 through 250 – 271 kg appeared to have higher risks compared to arrival weight categories 272 – 317 through > 362 kg (Figure 4.8). The 250 – 271 kg cohorts appear to have lower risk for arrival months of November through May than they did during arrival months of June through October. Cohorts in the < 182 through 228 – 249 kg arrival weight categories showed a very similar monthly risk pattern to the 250 – 271 kg weight cohorts (Figure 4.8). The combined mortality and culling risk for heavier arrival weight categories appeared to be more consistent across arrival months than the risk for the lighter weight cattle (Figure 4.8).

Discussion

Mortality risks for feedlot cattle have been discussed previously (Kelly and Janzen, 1986; Vogel and Parrott, 1994; Loneragan, 2004), but ours is the first study to use multivariable methods to quantify the effects of multiple common risk factors and to assess the combination of culling and mortality in large, commercial feedlot cattle populations. To our knowledge, there are no published reports on multivariable assessments of factors affecting culling or combined mortality and culling. Previous research on mortality risks was performed using only one or a limited number of feedlots, or utilizing data aggregated by feedlot on a monthly basis (MacVean

et al., 1986; Ribble et al., 1998; Loneragan et al., 2001). Using a limited number of feedlots for analysis limits the external validity of results because feedlots may differ in terms of management, cattle demographics, environmental and pathogen factors. Although our study population was not chosen randomly, we did utilize data from multiple feedlots that were generally similar to other commercial operations in the studied region of the U.S. Analyzing data aggregated at the feedlot level leads to loss of potentially important information regarding cohorts within a feedlot. With data aggregated at the feedlot level it is impossible to quantify the effects of lower level risk factors (e.g., arrival weight and gender of the cohort); that is, the levels at which feedlot managers often make decisions. The structure of our data enabled us to perform an analysis at the cohort-level and further allowed us to utilize multivariable approaches to quantify the effects and interactions of cohort-level risk factors that have not been previously described.

Our descriptive results for mean mortality (1.5%) and culling risks (0.7%) were similar to earlier reports utilizing feedlot data from the United States Department of Agriculture's National Animal Health Monitoring System where mean mortality risk was reported at 1.26% and mean culling risk ranged from 0.07% to 0.42% (Frank et al., 1988; Loneragan et al., 2001). Others have stated that mortality risk can reach as high as five percent when freshly weaned animals six to eight months of age enter the feedlot (Smith et al. 2001). However, our data indicate that cumulative mortality and culling on rare occasions are much higher than five percent; our maximum values were 31.9% for mortality and 100% for culling.

Feedlot mortality has been assessed in several studies, but both mortality and culling within cohorts have yet to be incorporated into a single outcome.   In our dataset, the ratios of mortality and culling within cohorts illustrate the variability in these adverse outcome measures among different feedlots over multiple years. Failing to account for culled animals could have profound implications on the estimates of animal losses in U.S. feedlots and on comparisons of health performance across feedlots and over time. These implication could be large, particularly if feedlots have differing criteria for culling animals, which could have direct and differential impacts on records for mortality (Loneragan, 2004).

Utilizing a large dataset containing cumulative feedlot data is useful for estimating cumulative measures of adverse health outcomes and assessing corresponding cohort-level risk factors. However, there were limitations to our current dataset as we were not able to assess

120

cause-specific mortality and culling, nor were we able to assess the timing at which death or culling occurred. Assessing cause-specific mortality and culling would allow us to quantify effects of separate risk factors for each potential diagnostic classification of mortality and culling. The timing of mortality and culling could have a large impact on feed and production costs depending on when during the feeding period an animal was lost due to mortality or culling. Others have demonstrated that the timing of adverse health events affects cattle performance and health measures (Babcock et al. 2009). One major limitation of utilizing operational data from multiple feedlot production system is the lack of consistent, standardized reporting of data across feedlots (Corbin and Griffin, 2006). There were only four potential risk factor variables that were collected across all 16 feedlots (gender, arrival weight, month, and year). Therefore, we could not evaluate factors that have been assessed in smaller-scale studies, such as the origin of animals or the feedlots' feed rations (Martin et al., 1982; Ribble et al., 1995).

Researchers have reported previously that feedlot mortality risks increased over time during the late 1990's and early 2000's (Loneragan et al., 2001; Loneragan, 2004; Babcock et al., 2006). We found similar results for arrival years 2000 – 2003, where there was an apparent increase in mortality and culling risk across these years (Figure 4.5). The 2006 study by Babcock and colleagues showed an increasing trend in mortality risk from 1992 through 2006. In our current study, mortality and culling risk appears to decrease subsequent to 2003 and then remain relatively constant from 2005 through 2007 (Figure 4.5). Our results may have differed because their earlier study used data aggregated across feedlots and arrival month. In addition, their data arose from a relatively small subpopulation of feedlots located in a single geographic location in Kansas (Babcock et al. 2006). Our current results are unique because we accounted for culled cattle and multiple covariates; potential confounders, when assessing mortality risks over time. Our results illustrate apparent temporal patterns in mortality and culling risk within and across years (Figure 4.4 and 4.5) after adjusting for these covariates. Combining culling and mortality data in a single outcome could result in a more precise estimate of animal losses in feedlots (Loneragan, 2004), and may provide results that are more robust to differential and non-static culling criteria. However, combining culling and mortality data into a single outcome does have disadvantages. We were unable to determine whether certain risk factors have different effects across these different outcomes. Further research on these issues could utilize

competitive risk analysis. For our current study, we wanted to quantify effects of risk factors associated with animal loss in feedlots, and combining culling and mortality data provides an outcome representing total animal loss.

Research assessing risk factors associated with mortality have found that female cohorts have higher mortality risk than male cohorts (Loneragan et al., 2001). We observed similar results in initial models of combined mortality and culling risk, but found the gender effect was modified by weight and arrival month. In general, it appears that females have higher risk of leaving the feedlot prematurely when arriving at both lighter ($<$ 227 kg) and very heavy weights ($>$ 362 kg) (Figure 4.6). The specific reasons for this effect modification cannot be determined in our study, but there are several feedlot management factors that differ between genders. As examples, male and female cattle are usually implanted with different growth promoters, female cattle rations often contain melengestrol acetate to prevent estrus, and females may be palpated and aborted unless they are confirmed as non-pregnant or spayed (Smith et al., 2001). Higher mortality and culling risk in light-weight females may be due to differences in these management factors, but could also be the result of biologic and physiologic differences between genders, or differential selection of genders at weaning. Female cohorts are at risk of exhibiting estrus during the feeding period, which may result in riding behavior causing lameness or other injuries, and light-weight cohorts have more days in the feedlot compared to heavier females and thus more days at risk to experience adverse health events leading to mortality and culling (Horton et al., 1979). Heifer replacement, through retaining or purchasing of animals, is essential to cow-calf producers. Therefore, feedlot placements are differential between genders as male calves primarily enter the feedlot production system, while some females may be retained as replacement heifers (Johnson, 2010). The selection of replacement heifers is based on several factors including weight at weaning, body capacity, structural soundness, health, and other important genotypic and phenotypic traits (Larson, 2005). Therefore, females with superior phenotypic and genotypic traits may go to cow herd replacement instead of feedlot production, resulting in inferior female cohorts entering the feedlot at light weights.

The high mortality and culling risk of females arriving $>$ 362 kg may be explained by complications due to parturition or abortion in females arriving at the feedlot pregnant, as these effects have been found to result in excessive and unpredictable death loss in heavier female feedlot cattle (Smith et al., 2001). One report estimated that 9% to 17% of females arrive at the

feedlot pregnant (Lechtenberg et al., 1998). In North America, the majority of pregnant females would arrive during the fall and winter months after they have been exposed to bulls on summer pastures (Sewell, 1993). This may be contributing to our observed apparent increase in cumulative mortality and culling risk for female cohorts arriving in August, September, and October (Figure 4.7).

Our large dataset allowed us to concurrently quantify effects of risk factors commonly collected by U.S. feedlots, and thereby providing information on separate effects that are impossible to estimate with smaller datasets (Ribble et al., 1995). Arrival weight and month are two common risk factors that are often difficult to separate due to the seasonal marketing patterns of feeder cattle in North America. The majority of light weight (often newly weaned animals) arrive at the feedlot in the autumn, and most heavier weight (yearling animals) arrive during the spring months; so, assessing these effects and potential interactions can be impossible with small datasets because of sparse data (Ribble et al., 1995).

Previous reports indicate that mortality risk in feedlots appears to be higher during fall months (Vogel and Parrott, 1994; Loneragan et al., 2001). Our results show higher combined mortality and culling risk for lighter weight cohorts (< 271 kg) during the summer and early autumn months (June – September), but for animals arriving at heavier weights (≥ 272 kg) there was very little month to month variation in risk (Figure 4.8). Literature cited above were from studies that did not utilize multivariable approaches to adjust for different types of cattle (e.g., arrival weight) at different times of year, which may have contributed to the differences from our results; also, may be simply due to our inclusion of culled animals in the outcome measurement. Our results indicate that as weight increases up to the 272 – 317 kg category, combined mortality and culling risk tends to decrease; however, once the 272 – 317 kg weight category is reached there appears to be little difference between weight categories across months. This indicates there may be no reason to price-distinguish across months with regard to combined mortality and culling risk between these heavier arriving cohorts.

For light-weight cohorts, combined mortality and culling risk appeared to differ across cohorts arriving in summer and winter months. Weight is often used as a proxy for the age of an animal on arrival at the feedlot; however, this may not always be the case. Approximately two-thirds of beef calves in the U.S. are born during the three-month period of February, March, and April, but feedlots are receiving light weight animals during all times of the year (Feuz and

123

Umberger, 2003). This could indicate that animals arriving at similar weights throughout the year may not always be the same age on arrival at the feedlot.   External factors such as drought or feed costs may impact the age at which cow-calf operations market and send calves to feedlots (Neville and McCormick, 1981). This may explain, in part, the high variability in risk that we observed across arrival months for lighter weight cohorts.

There also are management differences between the autumn and winter months that may be contributing to increased combined mortality and culling risk for cattle arriving during the early autumn (September and October) when compared to winter months (January and February). During the autumn months, a large population of freshly weaned animals, and animals derived from auction markets are arriving at the feedlot and the production system resources, including labor, may become overwhelmed resulting in higher levels of treatment failures (Thomson and White, 2006).

Another factor potentially contributing to the variability in combined mortality and culling risk among light arriving cohorts may be that weather differentially affects light weight cattle cohorts as compared to heavier cohorts. Light cattle arriving in the winter (cooler weather) appeared to have relatively low mortality and culling risk compared to similar weight cohorts arriving in the summer and early autumn (hotter temperatures). Decreases in ambient temperature during time of arrival at Canadian feedlots have been found to be associated with bovine respiratory disease case-fatality risk (Ribble et al., 1998); however, our results instead demonstrate that cohorts arriving during the hottest part of the year experienced the highest combined mortality and culling risks. The Canadian study assessed changes in ambient temperature post-arrival and effects specific to respiratory disease case-fatality (Ribble et al., 1998); whereas our study assessed all-cause combined mortality and culling and only assessed the effect of arrival month, not temperature specifically. Our results indicate the need for more research on the effects of management or environment conditions that impact adverse feedlot cattle health. Understanding these relationships may lead to the development of better management or purchasing practices for different types of cattle arriving throughout the year.

Conclusion

We quantified the effects of several cohort-level risk factors for combined mortality and culling risk utilizing cumulative data commonly available in the feedlot industry. Interactions

among effects, such as arrival month and arrival weight, have been discussed anecdotally in the literature, but have never been quantified for multiple arrival month and weight combinations. The effect modification and potential for confounding illustrate the importance of multivariable approaches when assessing data on heterogeneous feedlot cattle populations. To provide more specificity in large scale assessments such as reported here, there would need to be more consistent, standard data among multiple feedlot production systems. Furthermore, our model estimated combined mortality and culling risks from data that were retrospective and we did not assess the ability to predict future risks for cattle cohorts at feedlot arrival. However, we have provided unique quantitative estimates for effects of risk factors that have not been previously reported, and the estimated effects from our analysis may be useful for feedlot risk managers assessing the costs of adverse health outcomes based on their available data.

Acknowledgements

References

Babcock, A.H., White, B.J., Dritz, S.S., Thomson, D.U., Renter, D.G. 2009. Feedlot health and performance effects associated with the timing of respiratory disease treatment. J. Anim. Sci. 87, 314-327.

Babcock, A.H., Jones, R., Langemeier, M., 2006. Examining death loss in Kansas feedlots. Beef Cattle Research Report of Progress. Kansas State University, Manhattan, KS, pp. 46-52.

Corbin, M.J., Griffin, D., 2006. Assessing performance of feedlot operations using epidemiology. Vet. Clin. N. Am. Food Anim. Pract. 22, 35-51.

Dohoo, I., Martin, W., Stryhm, H., 2003. Veterinary Epidemiologic Research. AVC Inc., Charlottetown, Prince Edward Island, pp. 473-498.

Feuz, D.M., Umberger, W.J. 2003. Beef cow-calf production. Vet. Clin. N. Am. Food Anim. Pract. 19, 339-363.

Frank, G.R., Salman, M.D., MacVean, D.W., 1988. Use of a disease reporting system in a large beef feedlot. J. Am. Vet. Med. Assoc. 192, 1063-1067.

Horton, G.M.J., Stricklin, W.R., Manns, J.G., Mapletoft, R.J., 1979. Intravaginal devices for feedlot heifers. J. Anim. Sci. 49, 915-918.

Johnson, R.J., 2010. Continued contraction in cow herd implies decreased beef production beyond 2010. In: United States Department of Agriculture, E.R.S. (Ed.), Washington, D.C.

Kelly, A.P., Janzen, E.D., 1986. A review of morbidity and mortality rates and disease occurrence in North American feedlot cattle. Can. Vet. J. 27, 496-500.

Larson, R.L., 2005. Replacement heifers. In: Chenoweth, P.J., and Sanderson, M.W. (Ed.), Beef Practice: Cow-Calf Production Medicine. Blackwell Publishing, Ames, pp. 127-150.

Lechtenberg, K.F., Smith, R.A., Stokka, G.L., 1998. Feedlot health and management. Vet. Clin. N. Am. Food Anim. Pract. 14, 177-197.

Liu, H., Davidson, R.A., Rosowsky, D.V., Stedinger, J.R., 2005. Negative binomial regression of electric power outages in hurricanes. J. Infrastruc. Sys. 11, 258-267.

Loneragan, G.H., 2004. Feedlot mortalities: epidemiology, trends, classification. In, Academy of Veterinary Consultants Summer Meeting. 32, 34-43.

Loneragan, G.H., Dargatz, D.A., Morley, P.S., Smith, M.A., 2001. Trends in mortality ratios among cattle in US feedlots. J. Am. Vet. Med. Assoc. 219, 1122-1127.

MacVean, D.W., Franzen, D.K., Keefe, T.J., Bennett, B.W., 1986. Airborne particle concentration and meteorologic conditions associated with pneumonia incidence in feedlot cattle. Am. J. Vet. Res. 47, 2676-2682.

Martin, S.W., Meek, A.H., Davis, D.G., Johnson, J.A., Curtis, R.A., 1982. Factors associated with mortality and treatment costs in feedlot calves: the Bruce County Beef Project, years 1978, 1979, 1980. Can. J. Comp. Med. 46, 341-349.

Neville, W.E., and McCormick, W.C. 1981. Performance of early and normal weaned beef calves and their dams. J. Anim. Sci. 52, 715-724.

Ribble, C.S., Meek, A.H., Janzen, E.D., Guichon, P.T., Jim, G.K., 1995. Effect of time of year, weather, and the pattern of auction market sales on fatal fibrinous pneumonia (shipping fever) in calves in a large feedlot in Alberta (1985-1988). Can. J. Vet. Res. 59, 167-172.

Ribble, C.S., Meek, A.H., Shoukri, M.M., Guichon, P.T., Jim, G.K., 1998. Risk factors associated with fatal fibrinous pneumonia (shipping fever) in feedlot calves. In, Proc. Am. Assoc. Bov. Pract. 31, 104-109.

Sewell, H.B., 1993. Heifers vs. steers in the feedlot. Agricultural Publication. University of Missouri-Columbia, Columbia, Missouri. GO2082.

Smith, R.A., Stokka, G.L., Radostits, O.M., Griffin, D.D, 2001. Health and production management in beef feedlots. In: Radostits, O.M. (Ed.), Herd Health: Food Animal Production Medicine. W.B. Saunders Company, Philadelphia, pp. 581-633.

Stata, 2007. Longitudinal/panel data. Stata Press College Station, TX., pp. 317-329

Thomson, D.U., White, B.J., 2006. Backgrounding beef cattle. Vet. Clin. N. Am. Food Anim. Pract. 22, 373-398.

Vogel, G.L., Parrott, J.C., 1994. Mortality survey in feedyards. The incidence of death from digestive, respiratory and other causes in feedyards in the Great Plains. Comp. Con. Ed. Pract. Vet. 16, 227-234.

Walter, S.D., Feinstein, A.R., Wells, C.K., 1987. Coding ordinal independent variables in multiple regression analysis. Am. J. Epidemiol. 125, 319-323.

Figure 4.1 Distribution of combined mortality and culling counts within cattle cohorts (n = 54, 416) ranging in size from 40 – 340 animals arriving at 16 U.S. feedlots between 2000 – 2007.
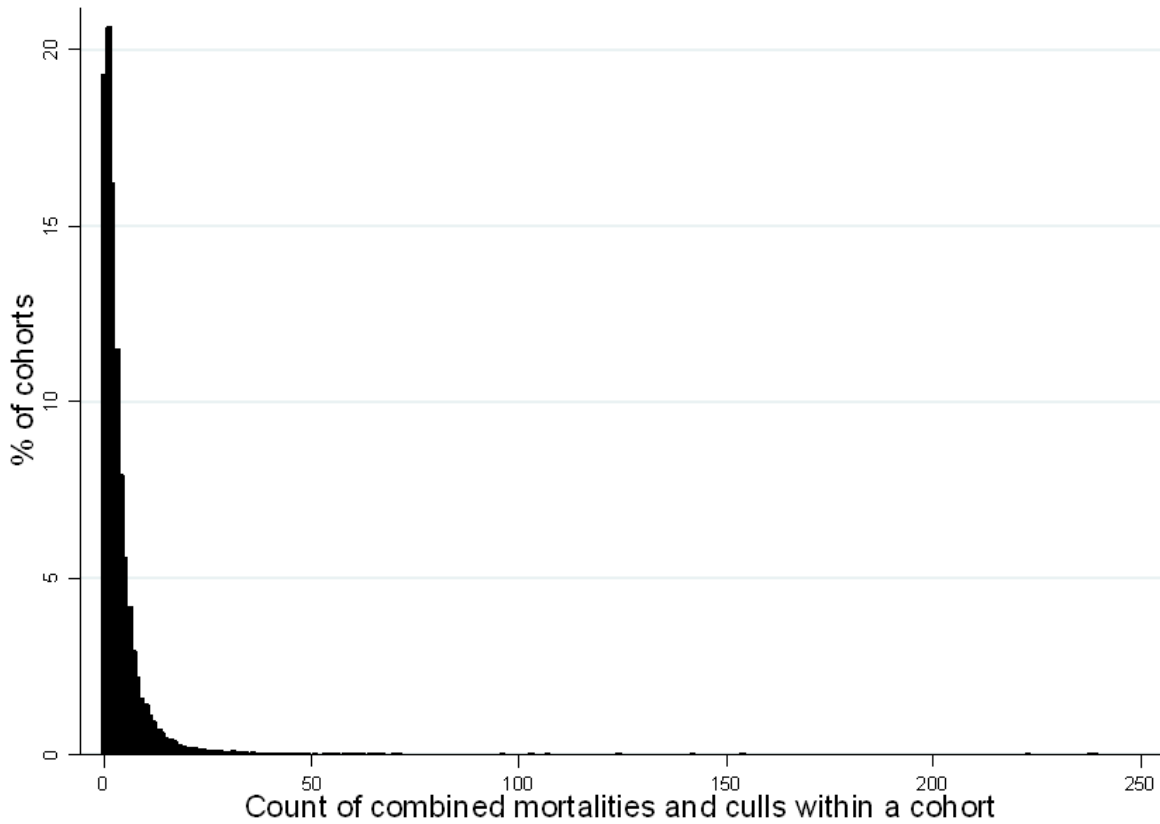
Figure 4.2 Probabilities for within-cohort counts of combined mortality and culling based on observed data and Poisson and negative binomial distributions (mean observed count = 3.56; Poisson overdispersion = 1.06)
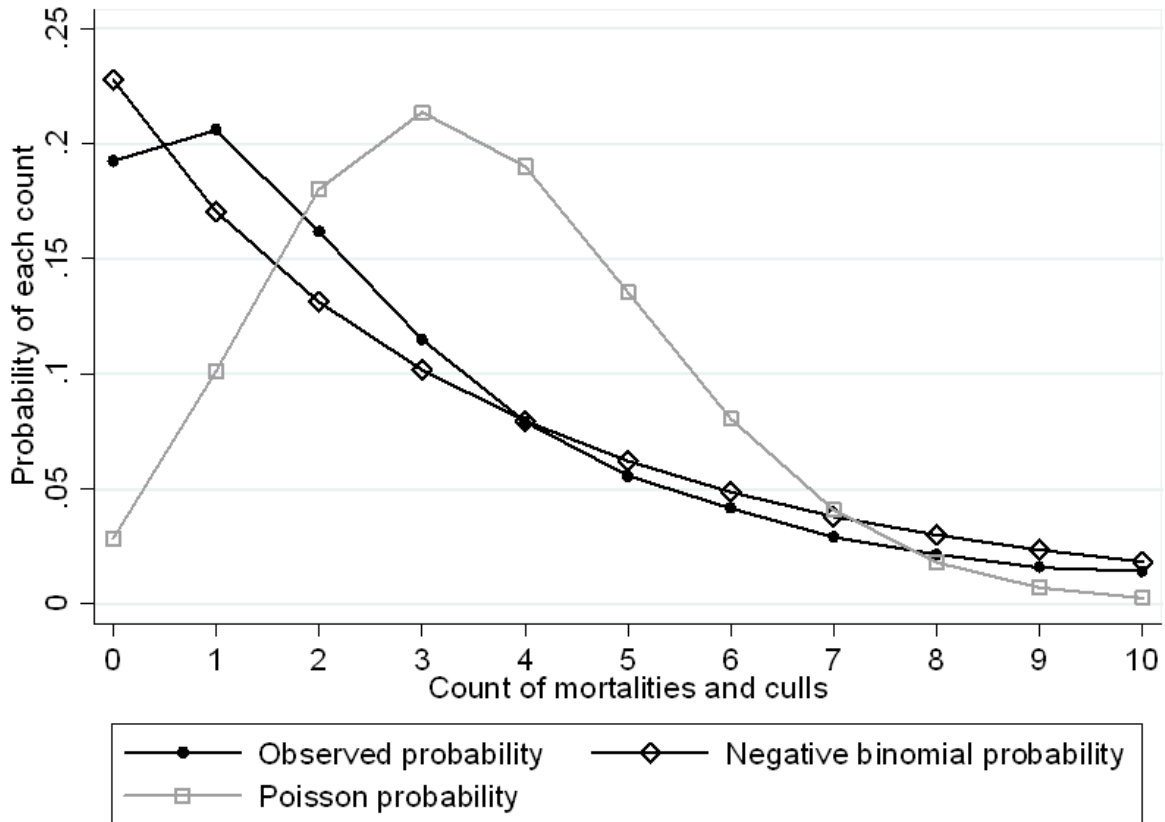
Figure 4.3 Observed minus predicted probabilities of counts from multivariable Poisson, negative binomial, and generalized negative binomial models of feedlot cattle combined mortality and culling (exposure = total cattle at risk within the cohort).
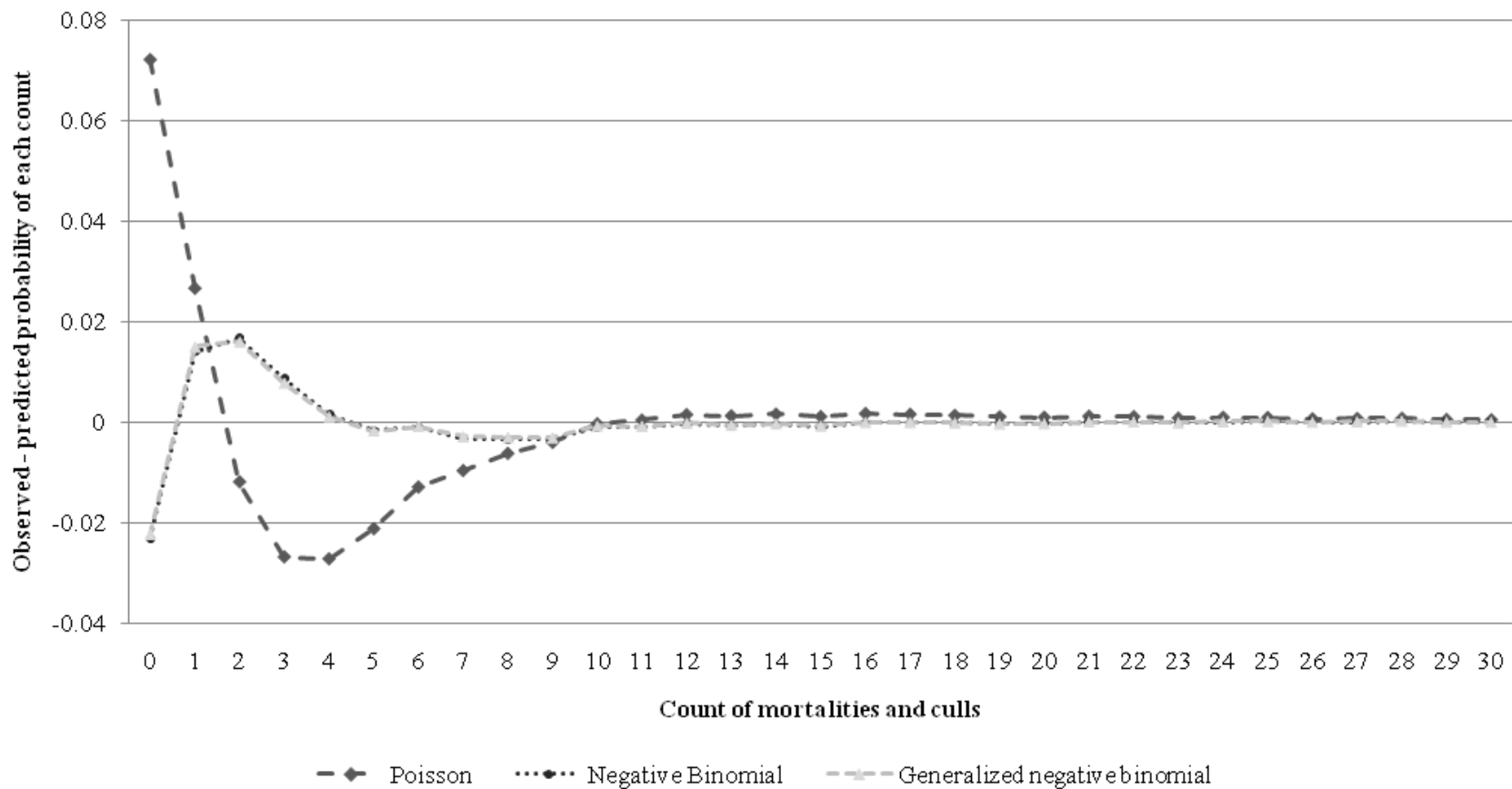
Table 4.1 Multivariable negative binomial mixed model[a] of combined mortality and culling risk for cohorts (n = 54,416) that arrived at 16 U.S. feedlots from 2000 – 2007.

Covariate	LR Test (*P*-values)	Levels	*b*	S.E. (*b*)	IRR	95% CI IRR	
Intercept			-4.42	0.03			
Arrival month	<0.00001	January	Referent				
		February	-0.11	0.04	0.89	0.82	0.97
		March	-0.17	0.05	0.85	0.77	0.92
		April	-0.21	0.05	0.81	0.73	0.89
		May	-0.33	0.04	0.72	0.66	0.78
		June	-0.07	0.04	0.94	0.86	1.02
		July	0.07	0.04	1.08	0.99	1.17
		August	0.00	0.04	1.00	0.93	1.08
		September	0.08	0.04	1.08	1.01	1.16
		October	0.10	0.03	1.10	1.03	1.18
		November	0.14	0.04	1.15	1.07	1.23
		December	0.20	0.04	1.22	1.14	1.32
Gender	0.2285	Steer	Referent				
		Heifer	-0.04	0.03	0.96	0.91	1.02
Arrival weight (kg)	<0.00001	< 182	0.31	0.16	1.37	0.99	1.89
		182 – 204	0.18	0.13	1.19	0.93	1.53
		205 – 227	0.06	0.09	1.06	0.88	1.26
		228 – 249	0.05	0.07	1.05	0.92	1.19
		250 – 271	0.01	0.06	1.01	0.91	1.13
		272 – 317	Referent				
		318 – 340	-0.18	0.04	0.83	0.77	0.90
		341 – 362	-0.34	0.04	0.71	0.65	0.77
		> 362	-0.54	0.05	0.59	0.53	0.64
Gender X arrival month	<0.00001	Male X (all months)	Referent				
		Female X January	Referent				
		Female X February	-0.01	0.04	0.99	0.91	1.08
		Female X March	-0.03	0.04	0.97	0.89	1.05
		Female X April	-0.10	0.05	0.91	0.83	0.99
		Female X May	-0.03	0.04	0.97	0.90	1.05
		Female X June	-0.13	0.04	0.88	0.81	0.95
		Female X July	-0.11	0.04	0.89	0.83	0.97
		Female X August	-0.06	0.04	0.95	0.88	1.02
		Female X September	-0.03	0.04	0.98	0.91	1.05
		Female X October	0.10	0.04	1.10	1.03	1.18
		Female X November	-0.06	0.04	0.95	0.87	1.02
		Female X December	-0.10	0.04	0.90	0.83	0.98
Arrival month X arrival weight (kg)	<0.00001	January X (all weights)	Referent				
		February X < 182	0.14	0.26	1.15	0.69	1.89
		February X 182 - 204	0.06	0.19	1.06	0.73	1.55
		February X 205 - 227	0.03	0.15	1.04	0.77	1.39
		February X 228 - 249	0.14	0.10	1.15	0.95	1.39
		February X 250 - 271	0.14	0.08	1.15	0.97	1.35
		February X 272 - 317	Referent				
		February X 318 - 340	0.00	0.06	1.00	0.90	1.12

February X 341 - 362	-0.01	0.06	0.99	0.88	1.12
February X >362	-0.06	0.07	0.94	0.82	1.07
March X < 182	0.87	0.21	2.40	1.59	3.62
March X 182 - 204	0.22	0.22	1.24	0.81	1.91
March X 205 - 227	0.45	0.16	1.56	1.15	2.12
March X 228 - 249	0.33	0.11	1.39	1.11	1.73
March X 250 - 271	0.12	0.09	1.13	0.95	1.36
March X 272 - 317	Referent				
March X 318 - 340	0.00	0.06	1.00	0.90	1.12
March X 341 - 362	0.02	0.06	1.02	0.90	1.14
March X >362	-0.02	0.06	0.98	0.86	1.11
April X < 182	0.86	0.21	2.36	1.57	3.56
April X 182 - 204	0.41	0.19	1.50	1.05	2.17
April X 205 - 227	0.36	0.14	1.44	1.09	1.90
April X 228 - 249	0.32	0.10	1.37	1.12	1.68
April X 250 - 271	0.31	0.09	1.37	1.15	1.62
April X 272 - 317	Referent				
April X 318 - 340	0.04	0.07	1.04	0.91	1.19
April X 341 - 362	0.03	0.07	1.03	0.90	1.18
April X >362	-0.02	0.07	0.98	0.86	1.12
May X < 182	0.73	0.18	2.07	1.45	2.95
May X 182 - 204	0.77	0.14	2.15	1.63	2.84
May X 205 - 227	0.69	0.11	1.99	1.61	2.45
May X 228 - 249	0.47	0.09	1.61	1.35	1.91
May X 250 - 271	0.43	0.08	1.54	1.32	1.78
May X 272 - 317	Referent				
May X 318 - 340	0.05	0.06	1.05	0.94	1.18
May X 341 - 362	0.11	0.06	1.12	1.00	1.26
May X >362	0.09	0.06	1.10	0.97	1.24
June X < 182	0.92	0.18	2.50	1.77	3.53
June X 182 - 204	0.91	0.14	2.48	1.90	3.26
June X 205 - 227	0.73	0.10	2.08	1.70	2.55
June X 228 - 249	0.72	0.08	2.05	1.74	2.41
June X 250 - 271	0.54	0.08	1.72	1.48	1.99
June X 272 - 317	Referent				
June X 318 - 340	-0.05	0.06	0.96	0.85	1.08
June X 341 - 362	-0.10	0.07	0.90	0.79	1.03
June X >362	-0.03	0.07	0.97	0.85	1.11
July X < 182	0.81	0.17	2.24	1.60	3.14
July X 182 - 204	0.72	0.14	2.06	1.57	2.69
July X 205 - 227	0.77	0.10	2.16	1.78	2.62
July X 228 - 249	0.53	0.08	1.71	1.46	2.00
July X 250 - 271	0.42	0.07	1.52	1.32	1.75
July X 272 - 317	Referent				
July X 318 - 340	-0.18	0.06	0.84	0.74	0.94
July X 341 - 362	-0.21	0.06	0.81	0.71	0.91
July X >362	-0.33	0.06	0.72	0.63	0.82
August X < 182	1.12	0.17	3.07	2.20	4.30
August X 182 - 204	0.69	0.14	1.99	1.52	2.60
August X 205 - 227	0.73	0.10	2.07	1.71	2.51

132

		August X 228 - 249	0.62	0.08	1.85	1.59	2.15
		August X 250 - 271	0.49	0.07	1.64	1.44	1.87
		August X 272 - 317	Referent				
		August X 318 - 340	-0.15	0.05	0.86	0.77	0.96
		August X 341 - 362	-0.17	0.06	0.84	0.75	0.94
		August X >362	-0.15	0.06	0.86	0.76	0.97
		September X < 182	0.47	0.18	1.60	1.12	2.28
		September X 182 - 204	0.70	0.14	2.02	1.55	2.64
		September X 205 - 227	0.56	0.10	1.76	1.45	2.13
		September X 228 - 249	0.49	0.07	1.64	1.41	1.89
		September X 250 - 271	0.32	0.07	1.38	1.22	1.57
		September X 272 - 317	Referent				
		September X 318 - 340	-0.17	0.05	0.84	0.75	0.94
		September X 341 - 362	-0.21	0.06	0.81	0.72	0.91
		September X >362	-0.19	0.06	0.83	0.73	0.94
		October X < 182	0.46	0.18	1.58	1.12	2.24
		October X 182 - 204	0.26	0.14	1.30	0.99	1.70
		October X 205 - 227	0.40	0.10	1.49	1.22	1.81
		October X 228 - 249	0.29	0.07	1.34	1.16	1.55
		October X 250 - 271	0.33	0.06	1.39	1.23	1.57
		October X 272 - 317	Referent				
		October X 318 - 340	-0.12	0.05	0.89	0.80	0.98
		October X 341 - 362	-0.16	0.06	0.85	0.76	0.95
		October X >362	-0.10	0.06	0.91	0.80	1.03
		November X < 182	0.29	0.18	1.34	0.94	1.90
		November X 182 - 204	-0.03	0.14	0.97	0.73	1.28
		November X 205 - 227	0.13	0.11	1.14	0.93	1.41
		November X 228 - 249	0.17	0.08	1.19	1.02	1.39
		November X 250 - 271	0.04	0.07	1.04	0.92	1.19
		November X 272 - 317	Referent				
		November X 318 - 340	-0.02	0.06	0.98	0.88	1.09
		November X 341 - 362	-0.10	0.07	0.91	0.80	1.03
		November X >362	0.03	0.07	1.03	0.89	1.19
		December X < 182	0.06	0.19	1.06	0.74	1.53
		December X 182 - 204	-0.10	0.15	0.91	0.68	1.21
		December X 205 - 227	-0.01	0.11	0.99	0.80	1.23
		December X 228 - 249	-0.05	0.08	0.95	0.81	1.11
		December X 250 - 271	-0.04	0.07	0.96	0.83	1.11
		December X 272 - 317	Referent				
		December X 318 - 340	-0.07	0.06	0.93	0.83	1.04
		December X 341 - 362	-0.08	0.07	0.92	0.81	1.05
		December X >362	-0.19	0.07	0.83	0.72	0.96
Gender X	<0.00001	Male X (all weights)	Referent				
Arrival weight (kg)		Female X < 182	0.02	0.05	1.02	0.92	1.13
		Female X 182 - 204	0.33	0.04	1.39	1.29	1.51
		Female X 205 - 227	0.18	0.03	1.20	1.13	1.28
		Female X 228 - 249	0.04	0.03	1.04	0.98	1.11
		Female X 250 - 271	0.07	0.03	1.07	1.01	1.13
		Female X 272 - 317	Referent				
		Female X 318 - 340	-0.07	0.03	0.94	0.89	0.98

133

Female X 341 - 362	-0.06	0.03	0.94	0.89	0.99
Female X > 362	0.34	0.03	1.40	1.32	1.50

[a]Random effect of both feedlot and arrival year ($P < 0.01$).

The estimates of the shape parameter $\ln(r)$ and scale parameter $\ln(s)$ were 2.65 and 3.28, respectively.

Figure 4.4 Model-estimated mean combined mortality and culling risk (%) within cattle cohorts (n =54,416) by month[a] they

**arrived at 16 U.S. feedlots during 2000 - 2007. Error bars represent 95% confidence intervals.**
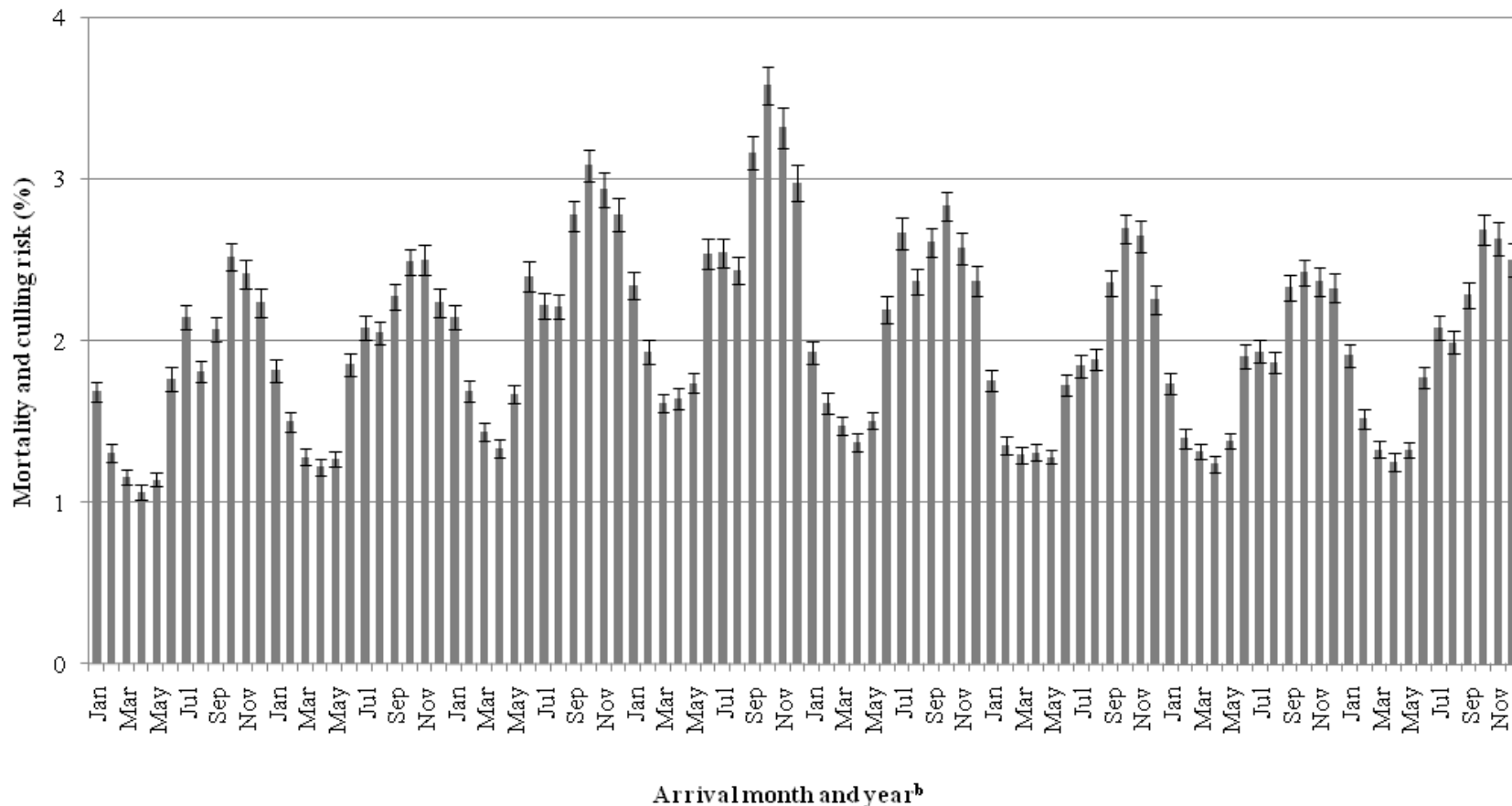
3

[a]Estimates from the final negative binomial model, where bars represent the marginal means across arrival years and arrival months. Effects not displayed in the
figure were included as a weighted average of the number of observations multiplied by the corresponding coefficient.
[b]On the x-axis arrival months are represented with an abbreviation (e.g., Jan = January, Mar = March, etc.)

135

7   **Figure 4.5 Model-estimated mean combined mortality and culling risk (%) within cattle cohorts (n = 54,416) by the year they**

8   **arrived at one of 16 U.S. feedlots [a]. Error bars represent 95% confidence intervals.**
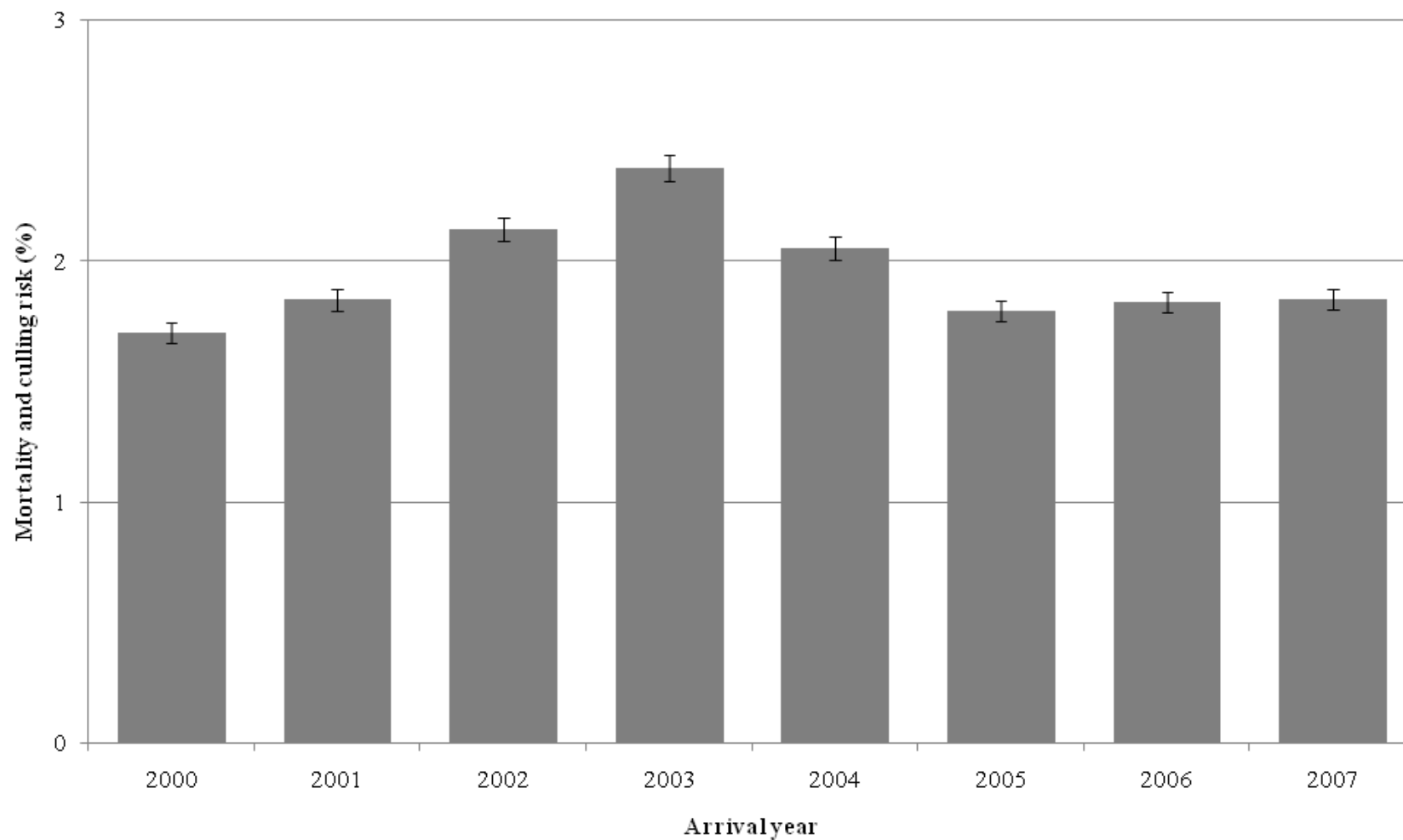
9

10   [a]Estimates from the final negative binomial model, where bars represent marginal means across arrival years. Effects not displayed in the figure were included as
11   a weighted average of the number of observations multiplied by the corresponding coefficient.

Figure 4.6 Model-estimated[a] mean combined mortality and culling risk (%) by gender (light grey = male, dark grey = female) and arrival weight categories (kg) for cattle cohorts (n =54,416) arriving at 16 U.S. feedlots from 2000 - 2007. Error bars represent 95% confidence intervals.
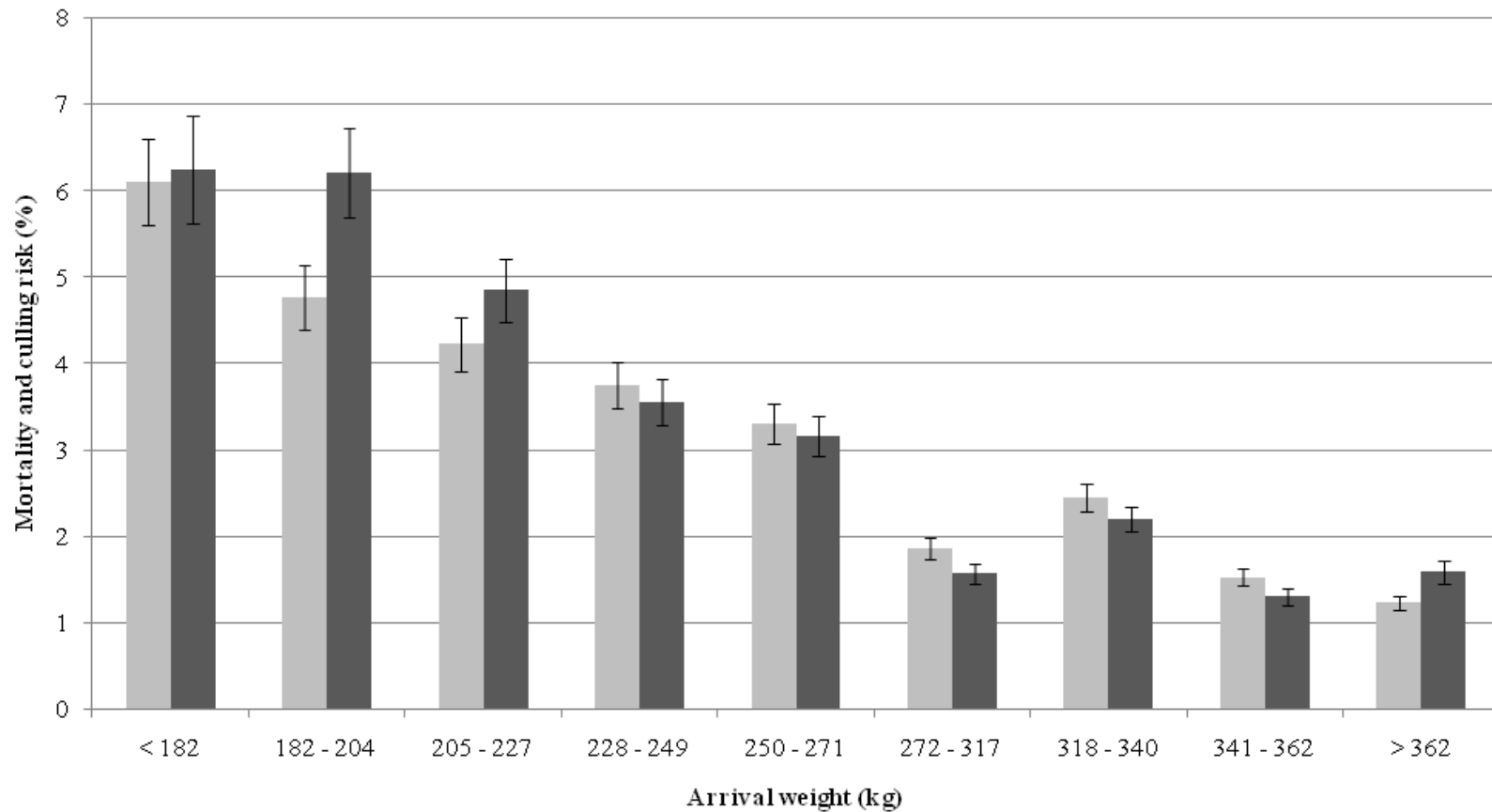
[a]Estimates from the final negative binomial mixed model, where bars represent the marginal means across arrival weight categories and gender. Effects not displayed in the figure were included as a weighted average of the number of observations multiplied by the corresponding coefficient.

Figure 4.7 Model-estimated[a] mean combined mortality and culling risk (%) by gender (light grey = male, dark grey = female) and arrival month for cattle cohorts (n =54,416) arriving at 16 U.S. feedlots from 2000 - 2007. Error bars represent 95% confidence intervals.
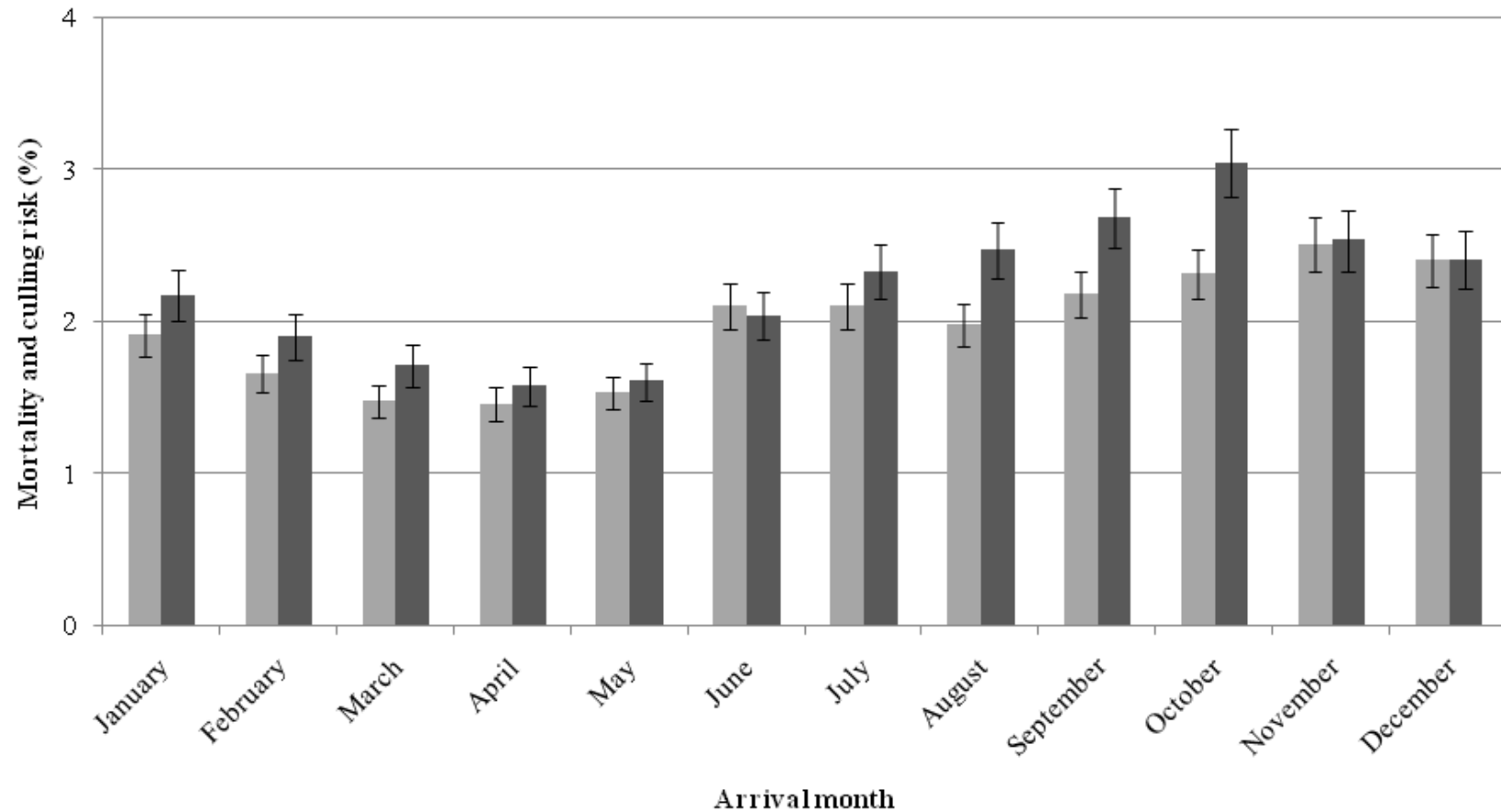
[a]Estimates from the final negative binomial mixed model, where bars represent the marginal means across arrival months and gender. Effects not displayed in the figure were included as a weighted average of the number of observations multiplied by the corresponding coefficient.

Figure 4.8 Model-estimated[a] mean combined mortality and culling risk (%) for cattle cohorts (n =54,416) arriving at 16 U.S. feedlots (2000 – 2007) by arrival weight category (kg) within arrival month. Error bars represent 95% confidence intervals.
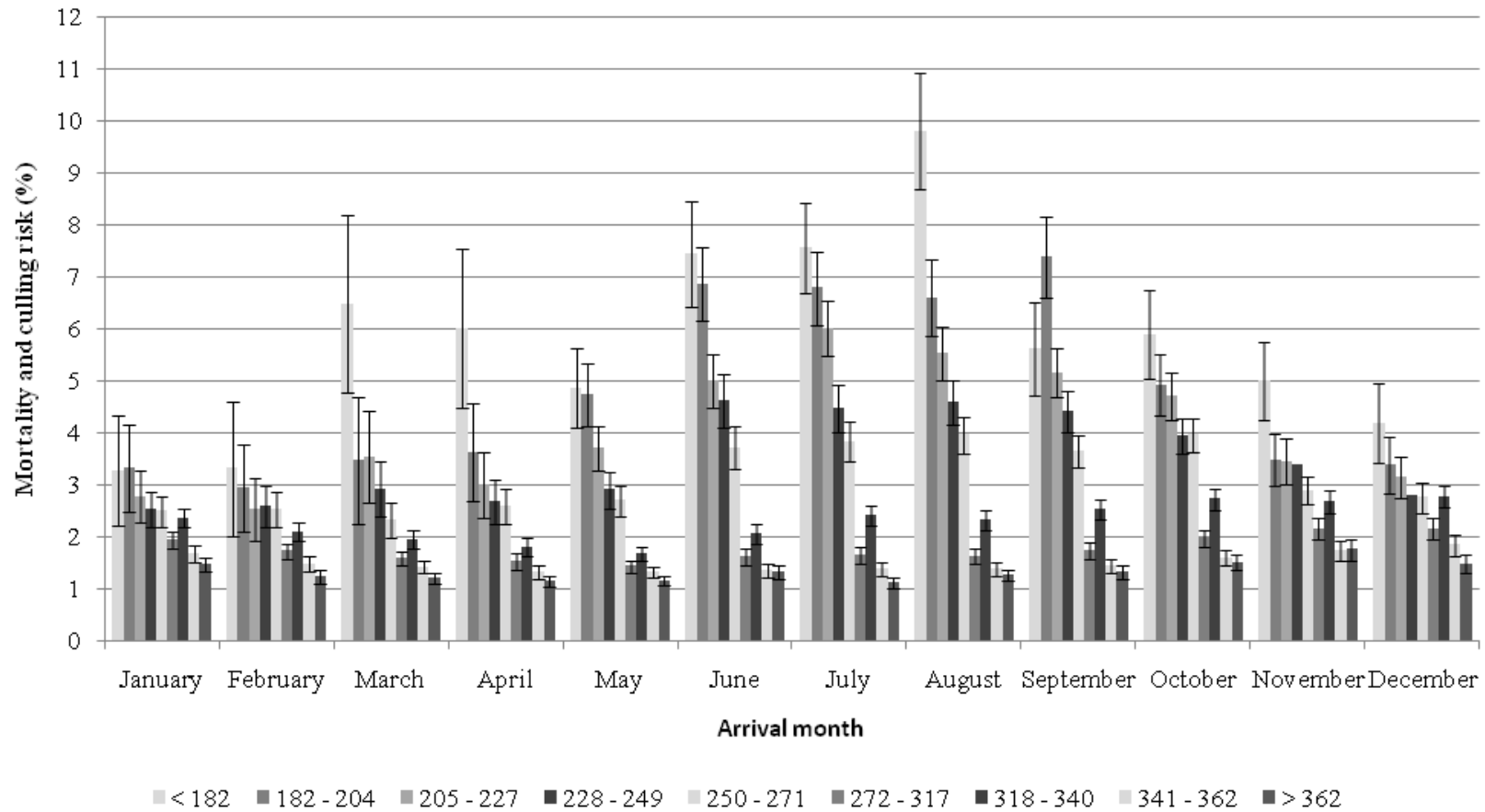
CHAPTER 5 - Predicting cumulative risk of bovine respiratory disease complex using feedlot arrival data and daily morbidity and mortality counts

A. H. Babcock[*,†], B. J. White[*], D.G. Renter[†], S.R. Dubnicka[#], and H.M. Scott[†]

[*]Department of Clinical Sciences, Kansas State University, Manhattan, KS, 66506

[†]Department of Diagnostic Medicine/Pathobiology

[#]Department of Statistics

Kansas State University, Manhattan, KS 66506

Abstract

Bovine Respiratory Disease Complex (BRDC) is the most common cause of post-weaning disease in cattle. Although the importance of accurately predicting health outcomes has been indicated, a formal analysis of BRDC prediction models using operational data from feedlots has not been documented in the literature. Our objectives were to assess the ability to predict cohort-level BRDC morbidity over the entire feeding period based on arrival risk factors, then to assess the value of adding daily BRDC morbidity data to the predictive models. We also wanted to evaluate the potential benefits of adding daily mortality data and BRDC risk classification (cohorts designated as high or lower risks by feedlot personnel). We used retrospective cohort-level and individual animal health data from 20 feedlots (2000 – 2009). We used mixed negative binomial regression models to predict cumulative BRDC morbidity for each of the first 30 days of the feeding period. Therefore, for each day we ran a new model that contained all arrival risk factors, in addition to the daily BRDC morbidity risk for that day and all previous days. Logistic regression models with generalized estimating equations were utilized to assess the probability of cohorts being correctly classified for cumulative BRDC risk within |5%|

across all days in the feedlot (arrival – day 30), while controlling for arrival month and cattle demographics (arrival weight and gender). The percent of correctly classified cohorts did increase across days of the feeding period, but the effect of day was modified by arrival weight, arrival month, and feedlot. Having information on the risk code of a cohort at arrival also appeared to significantly increase prediction over the first 10 days. Daily mortality risk displayed little to no benefit in prediction for 30 day study period. Our results are the first to demonstrate the ability of data commonly collected at commercial feedlots for predicting BRDC. We have shown that the predictive performance varied among feedlots, months, and cattle types.

Key Words: bovine respiratory disease complex, cattle, feedlot, negative binomial regression, predictive model

Introduction

Each year in the U.S., bovine respiratory disease complex (BRDC) costs the feedlot industry millions of dollars, and it remains the most common cause of post-weaning disease in beef cattle (Vogel and Parrott, 1994; Edwards, 1996; Smith, 1998). Accurately predictions of cattle production outcomes are essential components to running a sustainable, modern feedlot (Booker et al., 2004). These predictions promote timely, proactive evidence-based management decisions and could help facilitate strategies to improve BRDC management, yet the standard practice in feedlot production systems is often qualitative and subjective processes based on retrospective analyses (Corbin and Griffin, 2006).   Research with regard to predicting BRDC has been primarily performed using only arrival risk factors to quantify their effects on cumulative (close-out) disease outcomes (Martin et al., 1982; Ribble et al., 1995; Sanderson et al., 2008). Feedlots routinely collect data at arrival and on daily health events, yet literature utilizing these data to build iterative prediction models is non-existent. Adding new health information each day cattle are at the feedlot, versus only utilizing information collected at arrival (e.g. arrival weight, gender), may help improve the ability of health and risk managers to accurately predict health outcomes.

Our objectives were to assess the ability of models built with arrival risk factors to predict cumulative BRDC morbidity over the entire feeding period; also, to assess whether additional data, including daily health events, enhance the predictive ability.

Materials and methods

We collected cohort-level and individual animal-level morbidity and mortality data on cohorts of cattle that arrived during 2000 – 2009 from 20 feedlots in 5 states (Colorado, Kansas, Oregon, Texas, and Washington). Cohorts were identified as a group or "lot" of animals that were purchased, managed, and marketed similarly, but may or may not have been housed in the same physical location (pen) for the duration of the feeding period. Individual daily BRDC counts were collected for each cohort across all feedlots, and daily mortality counts were collected for 10 of the 20 feedlots. Daily health data were collected for the entire feeding period for each cohort, but we only used data on the first 30 days starting with the day the cohort arrived to the feedlot. A BRDC case was defined as an animal initially demonstrating clinical signs of BRDC (as determined by trained feedlot personnel) and treated with an antimicrobial. Mortality was defined as any animal that died due to any cause during the first 30 days of the feeding period. Cohort-level variables collected in all feedlots were: mean weight on arrival to the feedlot, gender, arrival month, and arrival year. Gender was assigned as male or female in the analysis, rather than steer or heifer because data on castration or pregnancy status at arrival to the feedlot were not available for all cohorts. A dichotomous variable "risk code" was reported for 10 of the feedlots, where feedlot personnel classified cohorts as "high" or "low" risk for BRDC following their standard protocols based on visual appraisal of animals at arrival, cattle source, transport time, and other factors. This practice attempts to qualitatively predict cumulative BRDC burden for a cohort of cattle at arrival, and is common in commercial feedlots (Lechtenberg et al., 1998).

Our study population was selected based on requirements that: feedlots reported both cohort-level and individual animal health data, cohorts arrived between 2005 and 2008, cohorts were classified as male or female (not mixed), cohorts initially contained between 40 to 340 animals, and cohorts had a mean arrival weight between 91 and 470 kg. The final study dataset included cattle from 20 feedlots. Ten of the feedlots had 1 additional arrival risk factor (risk code), but lacked daily mortality counts, while the other 10 feedlots had daily mortality counts, but not risk code. Therefore, we had 1 full dataset and 2 subsets for analysis. The full dataset consisted of 25,432 cattle cohorts from 20 feedlots, with data on arrival month, arrival year, mean arrival weight, gender, feedlot identifier, and daily morbidity counts from the first 30 days on feed. The second dataset (subset 1) had 14,100 cohorts from 10 feedlots with data on arrival

month, arrival year, mean arrival weight, gender, feedlot identifier, daily morbidity counts from the first 30 days on feed, and risk code. The third dataset (subset 2), also a subset of the full dataset, but with unique observations from those in subset 1, included data on 11,332 cohorts from 10 feedlots with factors of arrival month, arrival year, mean arrival weight, gender, feedlot identifier, daily morbidity counts from the first 30 days on feed, and daily mortality counts from the first 30 days on feed.

Data partitioning

To evaluate the predictive performance of negative binomial regression models on cumulative morbidity, data were randomly partitioned into 3 parts (training, validation, and test data) using the uniform distribution function of Stata version 10 (Stata Corp, College Station, TX, USA) (Berry and Linoff, 2004). The full dataset was used to randomly assign half of the observations to training and one-quarter of the observations to the validation and test datasets. Following the random partitioning of the full dataset, subset 1 and subset 2 were created by selecting the feedlots that reported risk code for subset 1, and feedlots that reported daily mortality counts for subset 2.

Descriptive statistics

Descriptive statistics were computed for all variables in the 3 datasets (training, validation, and test). For interval scale variables, minima, maxima, and quartiles were computed. Frequency tables were compiled for nominal variables. Prior to modeling building the NBVARGR procedure of Stata version 10 was used to plot probabilities for within cohort counts of cumulative BRDC morbidity based on observed data and Poisson and negative binomial distributions for the full training dataset.

Predictive model building

Predictive model building was split into 4 stages: 1) model selection using the full training dataset 2) model building using the full training dataset 3) model evaluation using the full validation dataset; and 4) obtaining final estimates using the full test dataset.

Model selection

The bivariable portion of the analysis was done using the NBREG procedure of Stata version 10, and the full training dataset utilizing risk factors collected at arrival for each cohort. For the initial stages of model building this procedure allowed for the comparison of negative binomial regression (NBR) to Poisson regression (PRM) utilizing a likelihood ratio test ($P <$ 0.05). Arrival month, year, and gender were analyzed on a nominal scale as reported by feedlots. Feedlot was also considered as a categorical independent variable for this portion of model building. The only independent variable collected on a continuous scale was arrival weight, but it did not meet linear assumptions. Arrival weight was broken into 22.7 kg (50 lb) categories, and 295 – 317 kg was used as the referent category, which corresponded to the most frequent feedlot arrival weight category.

Likelihood-ratio tests comparing the full model to the reduced model were utilized for all stages of model building (Dohoo et al., 2003a). Manual backward selection was used to fit main effect models (using $P < 0.05$ to remain in the model) with covariates that were associated ($P <$ 0.1) with the outcome in the bivariable models. Two-way interactions among arrival month, arrival weight, and gender were fit subsequent to the main effect model using backward selection ($P < 0.05$). Arrival year and feedlot were not included in any 2-way interactions as these were considered random variables and were to be included as random effects in the second stage of model building. Internal validity of the model was assessed using observed minus predicted probabilities, standardized deviance residuals, and Bayesian information criteria (BIC).

Subsequent to the determination of the final arrival risk factor model for the full training dataset, cumulative BRDC morbidity NBR models were developed for each day of the study period (days on feed 0 – 30). These models included the same model specification as the model developed for arrival risk factors, with the addition of daily BRDC risk (percentage) for each day. For example, the day 2 model would have all arrival risk factors in addition to daily BRDC risk for day 1 and day 2. Daily BRDC risk was defined as the total number of BRDC cases for each day within a cohort divided by the number at risk each day. The population at risk changed each day as number of BRDC cases the prior day were subtracted from the population at risk for the current day. Each model (day 0 – day 30) was assessed using observed minus predicted probabilities, standardized deviance residuals, and BIC. Polynomials (e.g. squared and cubed terms) were assessed for each new continuous variable added to the daily models (e.g. daily BRDC risk for day 0). However, Lowess plots of cumulative morbidity risk and daily BRDC

risk demonstrated a high proportion of cohorts on any given day that that had zero daily BRDC risk and a large range of values for cumulative BRDC morbidity risk, in which a squared or cubic term would be of no benefit. The relationship appeared to be linear for cohorts that demonstrated > 0% daily BRDC morbidity across cumulative BRDC morbidity risks.

Model building

Following to the determination of the NBR as the appropriate model, a mixed negative binomial regression (MNBR) model was assessed (XTNBREG, Stata version 10) using the full training dataset for arrival risk factors and all daily models. The procedure allows for 1 panel variable for random variables, which was used to account for the over-dispersion caused by lack of independence among cattle cohorts within arrival years and feedlots. The panel variable was specified to account for both year (n = 3) and feedlot (n = 19 in 2006, 20 in 2007, and 19 in 2008) concurrently; thus, the 2 variables were combined to create 58 categories. Independent variables were fit utilizing manual backward selection methods described above. To test the significance of the panel estimator compared to the pooled estimator of the NBR model a likelihood ratio test was performed, giving a formal statistical test of model fit between the MNBR and NBR (Stata, 2007). Shrinkage was determined was determined using the heuristic formula, as an indication of over fitting of the model (Steyerberg, 2009b).

Model evaluation

The full validation dataset was then run through the MNBR models determined above to assess model performance, and predicted probabilities were generated for each cohort in the full validation dataset for each of the models. A new variable was then created for observed cumulative morbidity minus the model predicted cumulative morbidity. This variable was generated for the arrival model as well as each day model (arrival and day 0 – day 30 models). The mean observed minus predicted values and standard deviations were calculated for each model, and then plotted. Cross-validation correlation values were also calculated (Kleinbaum et al., 2008). Subsequent to the assessment of the plot of mean observed minus predicted values and cross-validation correlation, modifications were made to the original model to determine if similar or better results could be obtained by removal of all 2-way interactions, and then 2-way interactions that were non-significant, but biologically plausible in the first model building procedures. Previous literature has indicated that the use of interaction terms can actually result

in predictive models performing worse, which is why different model specifications were attempted (Steyerberg, 2009a).

Obtaining final estimates

Following the determination of the final model, the full test dataset was run through the final model. Again predicted risks were generated for each cohort in the full test dataset, and the mean observed minus predicted values and standard deviations were calculated for each model, and then plotted in a figure. The cross-validation correlation values were also calculated.

Subsequent to the evaluation of the figure plotted above, a new binary variable that represented whether or not the cohort was correctly classified within |0.05| of observed minus predicted risks was created for each model (arrival – day 30). The new columns of data were used in a subsequent analysis examining the predictive ability of the model across different arrival risk factors (e.g., day, month, arrival weight, gender).

Predictive models subsets 1 and 2

Subset 1 and 2 were both subsets of the full dataset, where subset 1 contained risk code, but not daily mortality counts and vice versa for subset 2. We wanted to evaluate if the addition of each new variable from the respective dataset improved the predictive performance of the model developed using the full training dataset. Therefore, the full model as determined utilizing the full training dataset, was used to model subsets 1 and 2 with the addition of risk code (subset 1) and daily mortality risk (subset 2) using each respective training dataset to obtain beta coefficients. The models were also estimated with training data from subsets 1 and 2 without risk code (subset 1) and daily mortality risk (subset 2), so the effect of each covariate could be directly compared to the predictive ability of models that included each covariate. Subsequent to running the models for each training dataset (arrival – day 30), the test data for subset 1 and 2 was run through the final models (subset 1 with and without risk code and subset 2 with and without daily mortality risk for the arrival model through the day 30 model), and predicted risks were estimated for each model within a cohort. The mean observed minus predicted values and standard deviations were calculated for each model, and then plotted.

As above, new binary variables indicating whether a cohorts cumulative BRDC risk was correctly classified within |5%|were created for each model with and without risk code (subset 1; arrival – day 30) and with and without daily mortality risk (subset 2; arrival – day 30),. These

146

variables were then used in subsequent analysis examining the predictive ability of the models among different combinations of arrival risk factors (e.g. day, month, arrival weight, gender).

Assessing predictive ability of MNBR models using logistic regression

To assess how well each of the above models (i.e. full test dataset, subset 1 test data, and subset 2 test data) predicted cumulative morbidity risk, logistic regression models with generalized estimating equations were used to evaluate the binary outcome: whether or not a cohort was correctly classified within |5%| (observed minus predicted risk). This approach allowed us to make statistical comparisons of how well our predictive models performed across the first 30 days on feed, by adding "day" as a covariate.

Following the generation of estimates for the MNBR models for each of the 3 test datasets (i.e. full, subset 1, and subset 2), we had data representing whether a cohort was correctly classified for each of the models. These data were then expanded so each row of data represented the results of each model for each cohort. For the full test dataset there were 32 rows for each cohort (arrival, day 0, day 1,…, day 30), and a column that included 1 (correctly classified) or a 0 (misclassified).

For the test datasets from subsets 1 and 2, each row again represented the results of each model for each cohort. The difference being that for these 2 datasets there were 64 rows of data for each cohort representing whether or not each model (arrival – day 30) with and without risk code (subset 1) and with and without daily mortality risk (subset 2) correctly classified cumulative BRDC risk. The expanded test datasets for subsets 1 and 2 also included a column called "model," that demonstrated which model the results were obtained from, that is with or without risk code for subset 1 and with or without daily mortality risk for subset 2.

Using the newly manipulated test data (full, subset 1, and subset 2), logistic generalized estimating equations (GEE) were utilized to assess the probability of cohorts being correctly classified across days in the feedlot (arrival – day 30), while controlling for classification differences across months of arrival and cattle demographics (e.g. weight and gender), and accounting for the lack of independence of cohorts across days using a panel variable of cohort with robust standard errors (XTGEE, Stata version 11). A logistic model was developed for the full test dataset, subset 1 test data, and subset 2 test data. All covariates considered for inclusion in the model building stages of the MNBR predictive model were included here. The additional

147

covariate of arrival head count (number of animals that arrived in each cohort) was considered for inclusion, as our model may have predicted better or worse based on the size of the cohort. Arrival year and feedlot were included as fixed effects, as hierarchical models with both repeated measures on cohort and random effects for year and feedlot would not converge.

The same model building strategies as were used for the NBR models were used to construct bivariable and main effect GEE models. Wald χ2 tests were used to assess the overall significance of variables, or groups of indicator variables and interaction terms. Arrival head count was collected on a continuous scale, but did not meet linear assumptions. Therefore, arrival head count was divided into five categories based on approximate truckload size. The average arrival weight of the full training dataset was 308 kg, so each truckload could have contained approximately 70 head. The five categories consisted of < 70, $70 - 140$, $141 - 210$, $211 - 280$, and > 280 head. Two-way interactions with day (independent variable of interest) were fit subsequent main effects models by utilizing manual backward selection (Dohoo et al., 2003b). Day was the only covariate where 2-way interactions were examined as we wanted to assess how well our predictive model classified cohorts across arrival months, feedlots, years, genders, arrival head counts, and weight categories. For the test data from subsets 1 and 2, one additional covariate and 2-way interaction with day was assessed. The effect that represented whether risk code was or was not included (subset 1) or if daily mortality risk was or was not included in the predictive MNBR model was also evaluated.

Results

Training data for the full dataset consisted of 12,735 cohorts, validation and test data had 6,221 and 6,476 cohorts, respectively. Subset 1 had 7,034 cohorts in the training data, and 3,497 in the validation and 3,569 in the test data. Subset 2 had 5,701 cohorts were in the training data, and 2,724 in validation and 2,907 cohorts in the test data. The distribution of cohorts and arrival characteristics across training, validation, and test data for each dataset appeared to be equally distributed (data not shown). Mean, median, and standard deviation of cumulative morbidity across datasets are reported in Table 1.

Predictive model selection full dataset

For the full training dataset, plots of the observed probability of counts compared to the expected probabilities based on Poisson and negative binomial distributions suggested that the negative binomial distribution was a better fit than the Poisson distribution for the arrival model (Figure 1). The likelihood ratio test examining the null hypothesis that the dispersion parameter (alpha) is equal to zero was significant (alpha = 0.980 and $\chi2(1) = 9.1e+04$; $P < 0.001$). This indicated that the count of BRDC morbidities was overdispersed, and the observed data are better modeled using NBR. Each of the daily models fit subsequent to the arrival risk factor model displayed the same significant effects and daily BRDC morbidity risk was also statistically significant ($P < 0.05$) (results not shown).

For the MNBR arrival risk factor model of the full dataset, all variables in the main effects model were statistically associated with cumulative BRDC risk. The final model included significant 2-way interactions of arrival month and gender, and arrival month and arrival weight (data not shown). The random effect for arrival year and feedlot was also statistically significant in the final model ($P < 0.001$). Shrinkage for this model was 0.99, indicating that there was no evidence of overfitting the model. In each model when adding the additional covariate of daily BRDC risk, the variable was highly significant with the exception of day zero.

Fitting different model specifications (e.g., with and without 2-way interactions) resulted in no improvement in the reliability of the model as judged by observed minus predicted probability plots and cross-validation correlation of the full validation data; therefore, the original model described above was considered the final arrival model (results not shown). Observed minus predicted probability plots generated using the full test data indicated that the mean value was very close to zero for all models (arrival – day 30), but there was high variability around the mean which appeared to decrease across days (Figure 2).

Predictive models subsets 1 and 2

For the test data from subset 1, the MNBR arrival risk factor model that included risk code demonstrated that all main effects and all 2-way interactions were significant ($P < 0.05$) with the exceptions of gender by arrival weight, and risk code by arrival weight; these two were left out of the final model. Shrinkage for this model was 0.98, indicating there was no evidence

of overfitting. For each of the daily models, daily BRDC risk was significantly ($P < 0.05$) associated with cumulative BRDC morbidity risk with the exception of day zero. The model for subset 1 which did not include risk code as a covariate had all main effects significant ($P < 0.05$) and all 2-way interactions significant ($P < 0.05$) with the exception of gender by arrival weight, which was not included in the final model. Shrinkage for this model was calculated to be 0.98, again indicating no overfitting of the model. Observed minus predicted probability plots for both sets' of models appeared very similar to those in Figure 2.

All main effects and 2-way interactions for test data from subset 2 were significant ($P < 0.05$) with the exception of gender by arrival weight. Shrinkage for the arrival model was 0.98 indicating the model was not overfit. For each day models, the majority of daily BRDC risks were significant, in addition to daily mortality risk. The model for the test data from subset 2 which did not include daily mortality risk for each day had all main effects significant ($P < 0.05$), in addition to all 2-way interactions with the exception of gender by arrival weight. Daily BRDC risks were significant ($P < 0.05$) the majority of day models. Shrinkage for this model was calculated to be 0.98, again indicating no overfitting of the model. The observed minus predicted probability plots for each set of models again appeared very similar to those in Figure 2.

Assessing predictive ability of MNBR models with logistic regression

Full test dataset

The point at which a cohort was considered correctly classified (observed minus predicted < |5%|) affected the percent of correctly classified lots proportionately across days. Therefore, when interpreting the results across days if the point considered correctly classified would have been lowered (e.g. within |2.5%| difference between observed and predicted) there would have been a decrease in percent correctly classified across days, and if the point would have been increased (e.g. |10%|) the percent correctly classified would have increased (Figure 3).

The bivariable model for the effect of day on percent correctly classified indicated an association ($P < 0.001$). Days 2 -30 had an increased ($P < 0.001$) percentage of correctly classified cohorts compared to arrival information. In the main effects model day, arrival weight, month, arrival head count, year, and feedlot were all associated with percent correctly classified ($P < 0.05$).

150

In the final model, there was significant effect modification of day by arrival month, arrival weight, and feedlot (Figures 4 and 5). Figure 4 demonstrates the effect modification between day and arrival months. In general the percent of correctly classified cohorts was lowest in October – December, but these 3 months exhibited the greatest increase in percent correctly classified from arrival – day 30. The percent of cohorts classified correctly was greatest at arrival for cohorts arriving in February – June, but the increase in percent correctly classified across days for these months was relatively small (approximately 10 percent) (Figure 4).

The effect modification between day and arrival weight is shown in Figure 5. The percent correctly classified is greatest for cohorts arriving to the feedlot between 341 and > 409 kg, with small marginal increases across days (Figure 5). The largest increase in percent correctly classified across days are cohorts arriving between < 182 and 295 kg, where in some instances percent correctly went from 20 percent to 50 percent from arrival through day 30 (Figure 5).

The percent of cohorts correctly classified across feedlots and days is highly variable, as some feedlots had a low percentage of correctly classified cohorts (arrival – day 30) and some had a much higher percentage of correctly classified cohorts (arrival – day 30) (results not shown). At arrival the percent of cohorts correctly classified ranged from approximately 20 percent to 80 percent (results not shown). By day 30 the range was from 50 to as high as 85 percent (results not shown).

Subset 1 test data

Day was associated with percent correctly classified in the bivariable analysis. Days 3 – 30 had an increased ($P < 0.001$) percentage of correctly classified cohorts compared to arrival information. In the main effects model day, arrival weight, risk code, month, arrival head count, year, and feedlot were all associated with the percent correctly classified ($P < 0.05$). The effect of day on percent correctly classified was modified by model, arrival month, arrival weight, and feedlot ($P < 0.05$). The model that included risk code as a covariate had a higher ($P < 0.001$) percentage of correctly classified cohorts over the first 10 days; thereafter the difference was approximately 0 for the rest of the days assessed (Figure 6). The effect modification of arrival month, arrival weight, and feedlot on day was very similar to those of the full test dataset (results not shown).

Subset 2 test data

In subset 2, the bivariable model for the effect of day on percent of cohorts correctly classified indicated an association ($P < 0.001$). Days 4 -30 displayed an increase ($P < 0.001$) in the percent of cohorts correctly classified compared to arrival information. In the main effects model day, arrival weight, month, year, gender, and feedlot all had a significant association with the percent of cohorts correctly classified. The final model demonstrated effect modification ($P < 0.05$) of day by model, arrival month, arrival weight, and feedlot. Even though the interaction between day and model was significant ($P < 0.05$), Figure 7 displays there was no real benefit from adding daily mortality risk in the predictive models. The adjusted means were essentially the same for the effects from arrival through day 30 (Figure 7). The effect modification of arrival month, arrival weight, and feedlot on day was very similar to those of the full test dataset (results not shown).

Discussion

Although qualitative and retrospective analyses tends to be the standard in feedlot production systems, previous literature indicates that accurately predicting health outcomes and analytically assessing available data is key to improving process performance and assuring timely feedback to feedlot personnel (Booker et al., 2004; Corbin and Griffin, 2006; Reneau and Lukas, 2006). Our study is the first to use commercial feedlot data collected on a daily basis to quantitatively predict BRDC cumulative morbidity within cohorts of feedlot cattle. Previously, others have attempted to predict truckloads of cattle with high BRDC mortality using arrival data, but did not describe how well their models performed (Ribble et al. 1998). There are several studies that have quantified the effects of risk factors on cumulative BRDC morbidity risk, but to our knowledge none have attempted to assess how well their multivariable models predict cumulative BRDC risk (Alexander et al., 1989; Sanderson et al., 2008; Step et al., 2008; Babcock et al., 2009).

The epidemiology of BRDC in feedlot production systems is complex with tremendous variability in disease expression, resulting from interactions among pathogen, host, and management factors (Martin et al., 1982; Ribble et al., 1995; Cusack et al., 2003). Our results demonstrate that BRDC risk is highly variable; in our data, 0 to 100 percent of animals within a cohort were treated for BRDC (Table 1). This variability was also apparent when evaluating

152

how our models performed at predicting cumulative BRDC morbidity across days of the feeding period. Across the first 30 days on feed, the mean differences between observed and predicted cumulative BRDC risk were very small; indicating that on average the model will predict well. However, the accuracy for predicting BRDC risk of the next individual cohort would be quite poor, as evidenced by the large the standard deviations that indicate the relatively large variability in how well the model predicts (Figure 2). For example, the difference of observed minus predicted risks at arrival ranged from negative 28 percent to 72 percent, with a mean of negative 0.5 percent. The standard deviations of the observed minus predicted risks appeared to decrease over days indicating that the variability in the models predictive ability decreased over the feeding period. The mean difference is relatively non-informative when assessing how well the model will predict on the next cohort, but the standard deviations provide insight into the percent of cohorts that would fall within a given level of precision.

Dichotimizing the results for cohorts across each model (e.g., arrival, day 0, day 1, day 2) allowed us to make statistical comparisons of the predictive models performance among days of the feeding period. This approach does have limitations as results were interpreted relative to the breakpoint that was used to determine if a cohort was correctly classified (e.g., |5%|); however, Figure 3 demonstrates that the breakpoint only affected where the percent correctly classified crossed the y-axis, and not the shape of the percent correctly classified over the feeding period. We felt dichotomizing and running a logistic model was easier than predicted minus observed risks for interpretation and visualization of predictive model performance. The negative binomial model predicted morbidity but was not restricted to predict discrete counts (integers), so it was unlikely that the prediction would be exactly the same as the observed count. Our long term goal was to provide information of value to cattle managers. Management decisions impacted by cumulative morbidity do not require an exact prediction of cumulative morbidity risk, and a prediction within 5 percent of the actual magnitude of disease burden within a cohort should provide the information necessary to implement appropriate management techniques.

The effect of adding daily morbidity on predictive accuracy of the model was modified by arrival month. Even after controlling for the effect of arrival weight, our predictive model performed worse at arrival during the autumn months (September through December) compared to other months during the year (Figure 4). Management differences for autumn may be contributing to the predictive models difficulty at correctly classifying cohorts during these

153

months. During autumn months, a large population of freshly weaned cohorts, and cohorts derived from auction markets are arriving at the feedlot and the production system resources, including labor, may become overwhelmed (Ribble et al., 1995; Thomson and White, 2006). The overwhelmed production system and multiple sources of cohorts with unknown health history may contribute to high variability in cumulative BRDC across cohorts with similar covariate patterns (i.e. arrival weight, arrival month, and gender), thus making the predictive ability of the model less reliable based on information available at arrival.

The increase in the percent of correctly classified cohorts across the study period (30 days) for cohorts arriving in autumn months indicate that information was gained when daily morbidity risks were added to the models (Figure 4). For example, cohorts arriving in October had only 30 percent of cohorts correctly classified at arrival, and by day 30, this increased to 60 percent. The reason for this increase may be attributed to the lack of knowledge about previous history (e.g. health and management) of these cohorts at arrival, and once daily information is available models are rapidly able to benefit. For a feedlot manager these results indicate that there is value in assessing arrival data, but also demonstrates the benefit of assessing cohorts throughout the feeding period. If predictive performance of models at arrival were to increase by collection and inclusion of other informative risk factors (e.g., preconditioned status, source), predictive cumulative morbidity models could be a valuable asset for feedlots during the busy autumn period allowing for better allocation of resources.

Although some months of the year started with a high percentage of lots correctly classified at arrival, adding daily morbidity risk still offered additional benefits. From January to September, the amount of information gained by adding daily morbidity risk to the model seemed to level off by day 10. For a large portion of the year, the models seem to classify cohorts fairly well at arrival (January through June), but adding the first 10 days of daily BRDC data resulted in an apparent increase of 7 to 19% in the number of lots correctly classified. Increasing the percent of correctly classified cohorts during the first 10 days of the feeding period could allow feedlot managers to make important management decisions.

The effect of adding daily morbidity on predictive accuracy of the model also was modified by arrival weight; the predictive models classified heavy cohorts (e.g., 318-340 through >409 kg) very well, but performed poorly in the light weight cohorts ($\leq$ 296-317 kg). Both the percent of cohorts correctly classified at arrival and the amount of information gained by adding

154

daily morbidity counts varied by cattle weight at arrival. Feedlot cohorts that enter the feedlot at lighter weights are generally accepted to be at higher risk for BRDC (Smith et al., 2001). In our data, these lighter weight groups also displayed high variability in cumulative BRD risk for cohorts with similar arrival characteristics as evidenced by the low percentage of lots correctly classified at arrival. Reasons for the increased risk of lighter weight animals is thought to be associated with age/maturity, source of cattle, previous management, and the amount of commingling prior to arrival (Smith et al., 2001). Management of animals prior to, and at arrival, has been found to contribute to variable BRDC cumulative morbidities (Step et al., 2008). Cumulative BRDC morbidity for light weight (approximately 200 – 300 kg) cohorts commingled at arrival has been approximately 20 percent, 11 percent for cohorts directly from the ranch, and approximately 40 percent for cohorts coming from auction barns (Step et al., 2008). These results would suggest that there is large variability in cumulative BRDC morbidity especially if prior health management is unknown; no information on previous health management was available in our dataset. This may be part of the reason that the arrival predictive model failed to consistently classify light weight cohorts correctly at arrival.

Once data on daily BRDC were included for the first 5 days, there tended to be a sharp increases in percent of cohorts correctly classified; indicating the daily data were contributing important information to the model. Even though the percent of correctly classified cohorts was low for light weight cohorts, we observed a sharp increase in the percentage over a short period of time (Fig 5.5) indicating that feedlot managers could gain substantial knowledge about these types of cohorts when assessing data collected post-arrival. For the heavier arriving cohorts, the information gained over the first 30 days was minimal at best, indicating arrival information alone was enough to accurately classify these cohorts (Figure 5). These heavy cohorts had the largest percent of correctly classified cohorts at arrival (approximately 90 percent), so there was little room for improvement over the 30 day study period. The percent correctly classified at arrival for heavy cohorts was probably related to the fact that the model could predict a really low risk (e.g. < 5 percent), and a large percent of cohorts would fall within plus/minus 5 percent since these cohorts tend to experience relatively low BRDC risk. Previous research utilizing individual animal data has found that heavier weight animals experience very low cumulative morbidity (3.76% for 364 – 408 kg, and 0.89 % for > 409 kg) (Babcock et al., 2009).

Knowledge of previous management practices and cattle source/type are beneficial in qualitatively assessing the potential magnitude of cumulative BRDC within a cohort of cattle (Lechtenberg et al., 1998). Our results support this concept, as the model that contained risk code as covariate displayed a higher percent of correctly classified cohorts for the first 10 days on feed as compared to the model that did not contain risk code (Figure 6). The benefit of risk code could be the result of knowledge regarding metaphylaxis status of the cohort, or factors such as source of the cattle (e.g., order buyers with good or bad history of BRDC risk). However, the advantage of having information on risk code at arrival appears to be transient, in that there appears to be substantial benefit early in the feeding period when little daily information is available, but little to no benefit is observed past day 15. On average, with or without risk code included as a covariate, the models classified cohorts correctly 70 percent of the time by the end of the 30 day study period. However, the benefit of including risk code in the model came early in the feeding period when feedlots could still adjust management decisions based on predictive model output. The increased performance of the predictive model with risk code early in the study period indicates that there is potential value when feedlots collect previous source and health history of cohorts.

The majority of BRDC morbidity (approximately 70%) takes place during the first 45 days of the feeding period, but only 40 percent of mortality takes place during the same time period (Smith et al., 2001). This may be a large reason why adding daily mortality risk to the predictive model did not appear to benefit the percentage of cohorts correctly classified during the first 30 days of the feeding period (Figure 7). It also may be that having information on one health event (daily morbidity) is enough, and adding another variable adds no benefit to the predictive ability of the models.

A potential limitation of this study is the use of operational feedlot data with the case definition of BRDC based on subjective clinical signs. The general criterion for the diagnosis of BRDC across the feedlot industry includes depression, elevated respiratory rate, and elevated body temperature (Sanderson et al., 2008). The case definition used in our study was broad, but based on consistently available data. Misclassification of both sick and healthy cattle may occur with BRDC case definitions, as research has shown that the sensitivity (62%) and specificity (63%) of diagnosing BRDC based on clinical criteria are relatively low (White and Renter, 2009). However, diagnosing BRDC in this manner is the industry standard and we are simply

156

reporting a measure of treatment risk, which is based on perceived morbidity (Sanderson et al., 2008).

In attempting to predict cumulative BRDC morbidity risk, we also added both arrival year and feedlot as random parameters to account for unmeasured differences in management practices resulting in overdispersion among feedlots and over time. The lack of consistent standardized reporting of data across feedlots can be a problem for analysis of commercial feedlot data (Corbin and Griffin, 2006). The only risk factors that were reported on a consistent fashion across all 20 feedlots were arrival weight, arrival month, arrival year, and gender. In our predictive MNBR model using the full dataset, we were unable to account for other potentially important variables such as preconditioned status (vaccination and weaning strategy), metaphylaxis, source of cattle, and nutritional status at arrival; all thought to influence cumulative BRDC morbidity (Duff and Galyean, 2007). However, in our predictive model using subset 1, we were able to include a variable indicating respiratory risk code, which might be considered a summary, proxy variable for many of these variables (Lechtenberg et al., 1998).

Conclusion

We assessed the ability to predict cumulative BRDC using commonly collected risk factors and daily health data, and found the predictive ability was highly dependent on the covariate pattern of the cohort. The regression models predicted well at arrival for types of cattle cohorts that are commonly considered low risk for BRDC morbidity.   For higher risk cattle, updating with daily morbidity data, particularly over the first 10 days on feed, enhanced the predictive performance of the models.   The addition of risk code to the models demonstrated the potential value of classifying cattle based on pre-arrival data. If more refined data regarding prior history of cohorts were collected, we may be able increase the predictive ability of models at arrival, thus increasing the utility of such models in commercial feedlot settings.

References

Alexander, B.H., MacVean, D.W., Salman, M.D., 1989. Risk factors for lower respiratory tract disease in a cohort of feedlot cattle. J. Am. Vet. Med. Assoc. 195, 207-211.

Babcock, A.H., White, B.J., Dritz, S.S., Thomson, D.U., Renter, D.G., 2009. Feedlot health and performance effects associated with the timing of respiratory disease treatment. J. Anim. Sci. 87, 314-327.

Berry, M.J.A., Linoff, G.S., 2004. Data Mining Techniques. Wiley Publishing, Inc. Indianapolis, IN.

Booker, C.W., Loneragan, G.H., Guichon, P.T., Kee, J.G., Schunicht, O.C., Wildman, B.K., Pittman, T.J., Fenton, R.K., Janzen, E.D., Perrett, T., 2004. Practical Application of Epidemiology in Veterinary Herd Health/production Medicine. In, AABP Proceedings, pp. 59-62.

Corbin, M.J., Griffin, D., 2006. Assessing performance of feedlot operations using epidemiology. Vet. Clin. North Am. Food Anim. Pract. 22, 35-51.

Cusack, P.M., McMeniman, N., Lean, I.J., 2003. The medicine and epidemiology of bovine respiratory disease in feedlots. Aust. Vet. J. 81, 480-487.

Dohoo, I., Martin, W., Stryhm, H., 2003a. Mixed Models for Continuous Data. Veterinary Epidemiologic Research. AVC Inc., Charlottetown, Prince Edward Island, pp. 473-498.

Dohoo, I., Martin, W., Stryhm, H., 2003b. Model-building strategies. Veterinary Epidemiologic Research. AVC Inc., Charlottetown, Prince Edward Island, pp. 317-334.

Duff, G.C., Galyean, M.L., 2007. Board-invited review: recent advances in management of highly stressed, newly received feedlot cattle. J. Anim. Sci. 85, 823-840.

Edwards, A.J., 1996. Respiratory diseases of feedlot cattle in the central USA. Bov. Pract. 30, 5-7.

Kleinbaum, D.G., Kupper, L.L., Nizam, A., Muller, K.E., 2008. Selecting the best regression equation. Applied regression analysis and other multivariable methods. Duxbury, Belmont, CA, pp. 383-419.

Lechtenberg, K.F., Smith, R.A., Stokka, G.L., 1998. Feedlot Health and Management. Vet. Clin. North Am. Food Anim. Pract. 14, 177-197.

Martin, S.W., Meek, A.H., Davis, D.G., Johnson, J.A., Curtis, R.A., 1982. Factors associated with mortality and treatment costs in feedlot calves: the Bruce County Beef Project, years 1978, 1979, 1980. Can. J. Comp. Med. 46, 341-349.

Reneau, J.K., Lukas, J., 2006. Using statistical process control methods to improve herd performance. Vet. Clin. North Am. Food Anim. Pract. 22, 171-193.

Ribble, C.S., Meek, A.H., Janzen, E.D., Guichon, P.T., Jim, G.K., 1995. Effect of time of year, weather, and the pattern of auction market sales on fatal fibrinous pneumonia (shipping fever) in calves in a large feedlot in Alberta (1985-1988). Can. J. Vet. Res. 59, 167-172.

Sanderson, M.W., Dargatz, D.A., Wagner, B.A., 2008. Risk factors for initial respiratory disease in United States' feedlots based on producer-collected daily morbidity counts. Can. Vet. J. 49, 373-378.

Smith, R.A., 1998. Impact of disease on feedlot performance: a review. J. Anim. Sci. 76, 272-274.

Smith, R.A., Stokka, G.L., Radostits, O.M., D.D.Griffin, 2001. Health and production management in beef feedlots. In: Radostits, O.M. (Ed.), Herd Health: Food Animal Production Medicine. W.B. Saunders Company, Philadelphia, pp. 581-633.

Stata, 2007. Longitudinal/Panel Data. Stata Press College Station, TX.

Step, D.L., Krehbiel, C.R., DePra, H.A., Cranston, J.J., Fulton, R.W., Kirkpatrick, J.G., Gill, D.R., Payton, M.E., Montelongo, M.A., Confer, A.W., 2008. Effects of commingling beef calves from different sources and weaning protocols during a 42-day receiving period on performance and bovine respiratory disease. J. Anim. Sci. 86, 3146-3158.

Steyerberg, E.W., 2009a. Assumptions in regression models: additivity and linearity. In: Gail, M., Krickeberg, K., Samet, J., Tsiatis, A., Wong, W. (Eds.), Clinical prediction models: A practical approach to development, validation, and updating. Springer Media, New York, NY, pp. 213-228.

Steyerberg, E.W., 2009b. Modern estimation methods. In: Gail, M., Krickeberg, K., Samet, J., Tsiatis, A., Wong, W. (Eds.), Clinical prediction models: A practical approach to development, validation, and updating. Springer Media, New York, NY, pp. 231-240.

Thomson, D.U., White, B.J., 2006. Backgrounding beef cattle. Vet. Clin. North Am. Food Anim. Pract. 22, 373-398.

Vogel, G.L., Parrott, J.C., 1994. Mortality survey in feedyards. The incidence of death from digestive, respiratory and other causes in feedyards in the Great Plains. Comp. Con. Ed. Pract. Vet. 16, 227-234.

White, B.J., Renter, D.G., 2009. Bayesian estimation of the performance of using clinical observations and harvest lung lesions for diagnosing bovine respiratory disease in post-weaned beef calves. J. Vet. Diagn. Invest. 21, 446-453.

Table 5.1 The mean, median, SD, minimum, and maximum cumulative bovine respiratory disease complex morbidity risk for each dataset

Dataset	Mean	Median	SD	Minimum	Maximum
Full[1]					
Training	8.6	4.2	11.4	0.0	94.7
Validation	8.7	4.3	11.3	0.0	98.4
Test	8.5	4.1	11.3	0.0	94.2
Subset 1[2]					
Training	7.6	3.7	10.3	0.0	94.7
Validation	7.7	3.7	10.5	0.0	98.4
Test	7.7	3.5	10.7	0.0	94.2
Subset 2[3]					
Training	9.8	4.9	12.4	0.0	91.2
Validation	9.6	4.9	12.0	0.0	73.0
Test	9.6	4.9	12.0	0.0	73.0

[1] n = 12,735

[2] n = 7,034

[3] n = 5,701

Figure 5.1 Probabilities for within cohort counts of bovine respiratory disease complex cases based on observed data and Poisson and negative binomial distributions (mean observed count = 10.81; Poisson overdispersion = 1.58)
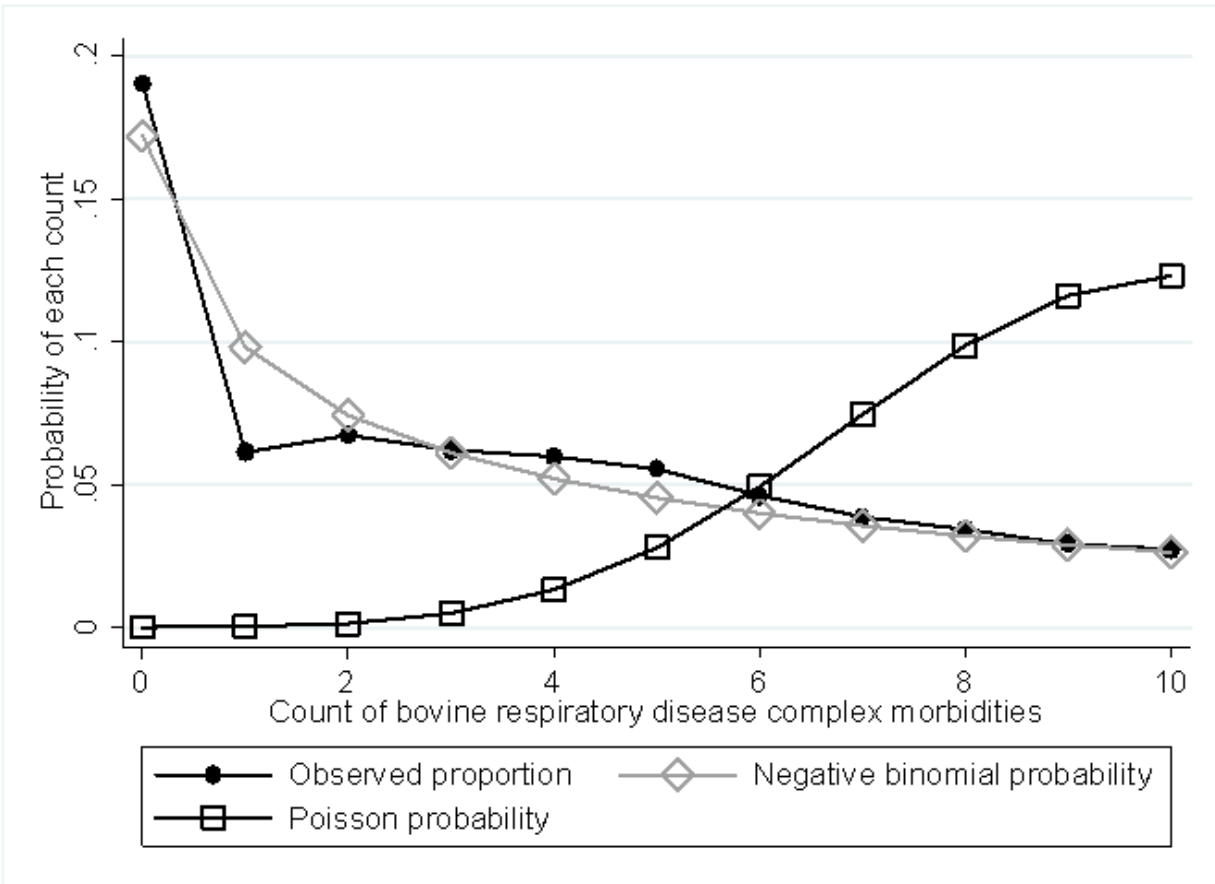
Figure 5.2 Mean observed minus predicted risks for the final mixed negative binomial regression models for the full test dataset (n = 6,476). Each day on the x-axis represents the results for each of the 32 models (arrival – day 30). Error bars represent 1 SD of the mean.
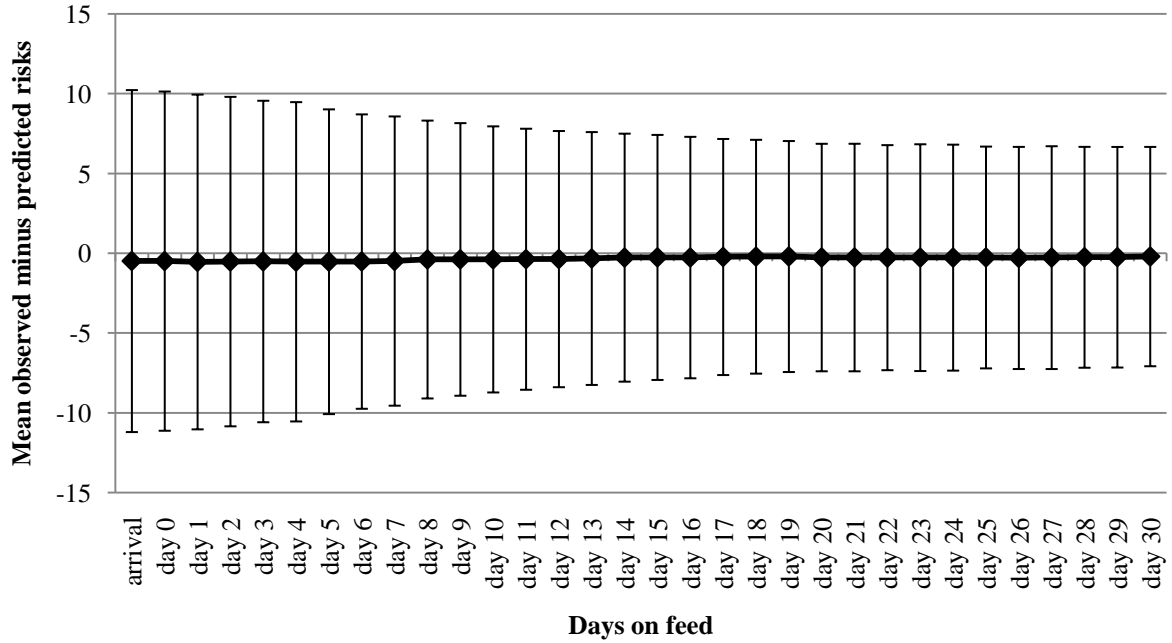
Figure 5.3 Mean percent of cohorts where cumulative BRDC morbidity was correctly classified by days for each of three observed minus predicted cumulative bovine respiratory disease complex break points (|2.5%|, |5%|, and |10%|) examined for the consideration of a cohort as correctly classified for the full test dataset; including 6, 476 cattle cohorts that arrived to 20 U.S. feedlots during 2006 – 2008.
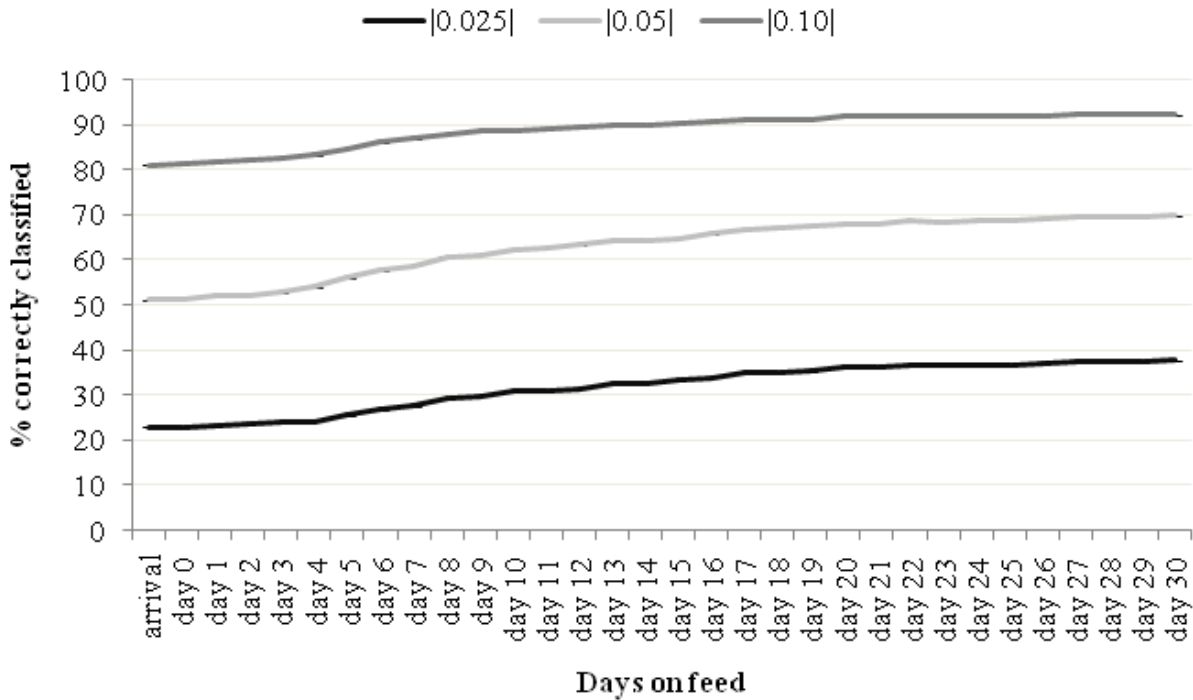
Figure 5.4 Model estimated[a] mean percent of cohorts where cumulative BRDC morbidity was correctly classified by month (each panel contains 3 months for visual purposes) and day (full dataset test data; n = 6,476) arriving to 20 U.S. feedlots from 2006 -2008. Error bars represent robust 95% confidence intervals.
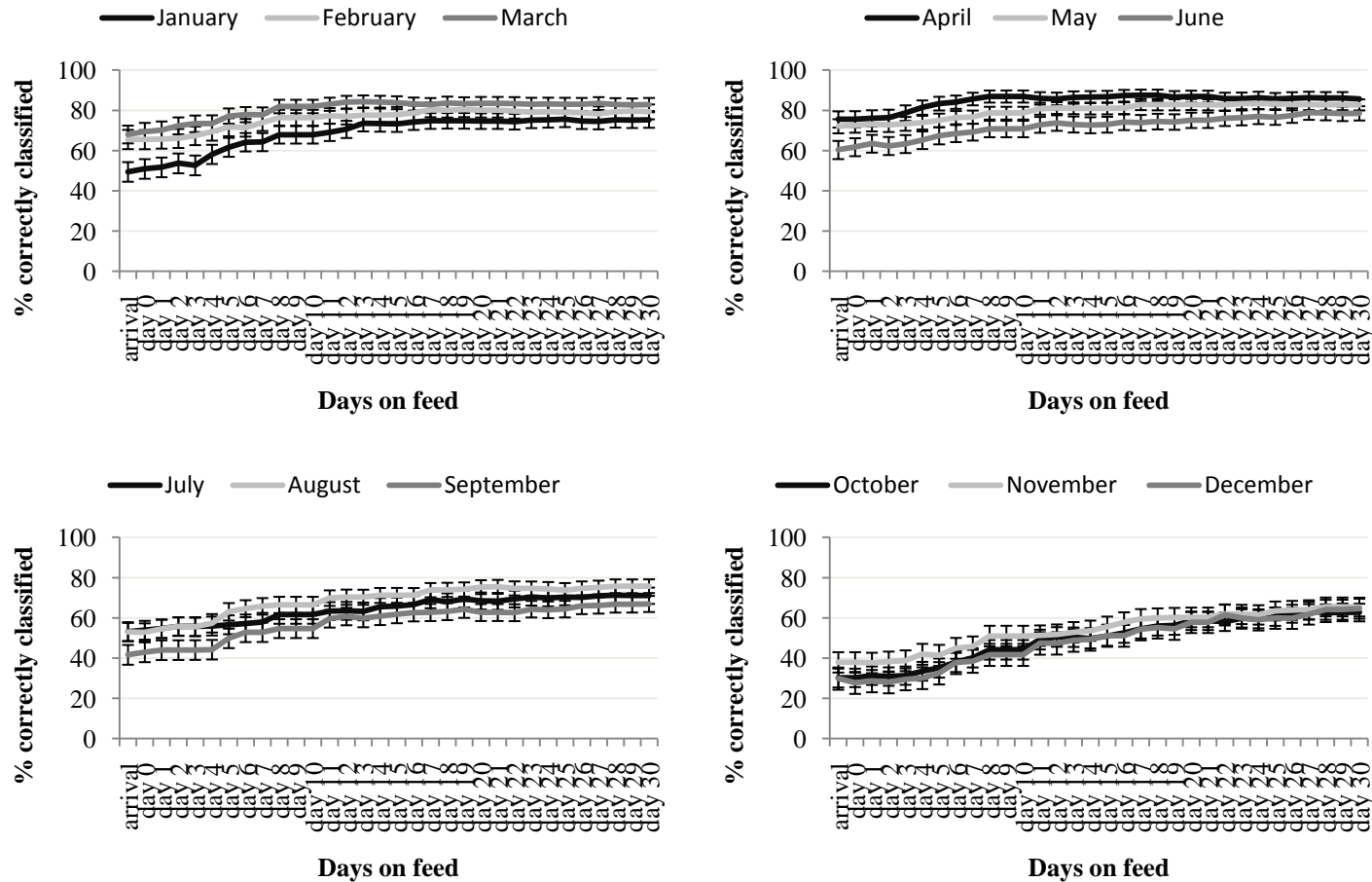
[a]Estimates from the final logistic generalized estimating equation, where lines represent the marginal means across days and arrival months. Effects not displayed in the figure were included as a weighted average of the number of observations multiplied by the corresponding coefficient.

Figure 5.5 Model estimated[a] mean percent of cohorts where cumulative BRDC morbidity was correctly classified by arrival weight category (each panel contains 3 weight categories for visual purposes) and day (full dataset test data; n = 6,476) arriving to 20 U.S. feedlots from 2006 -2008. Error bars represent robust 95% confidence intervals.
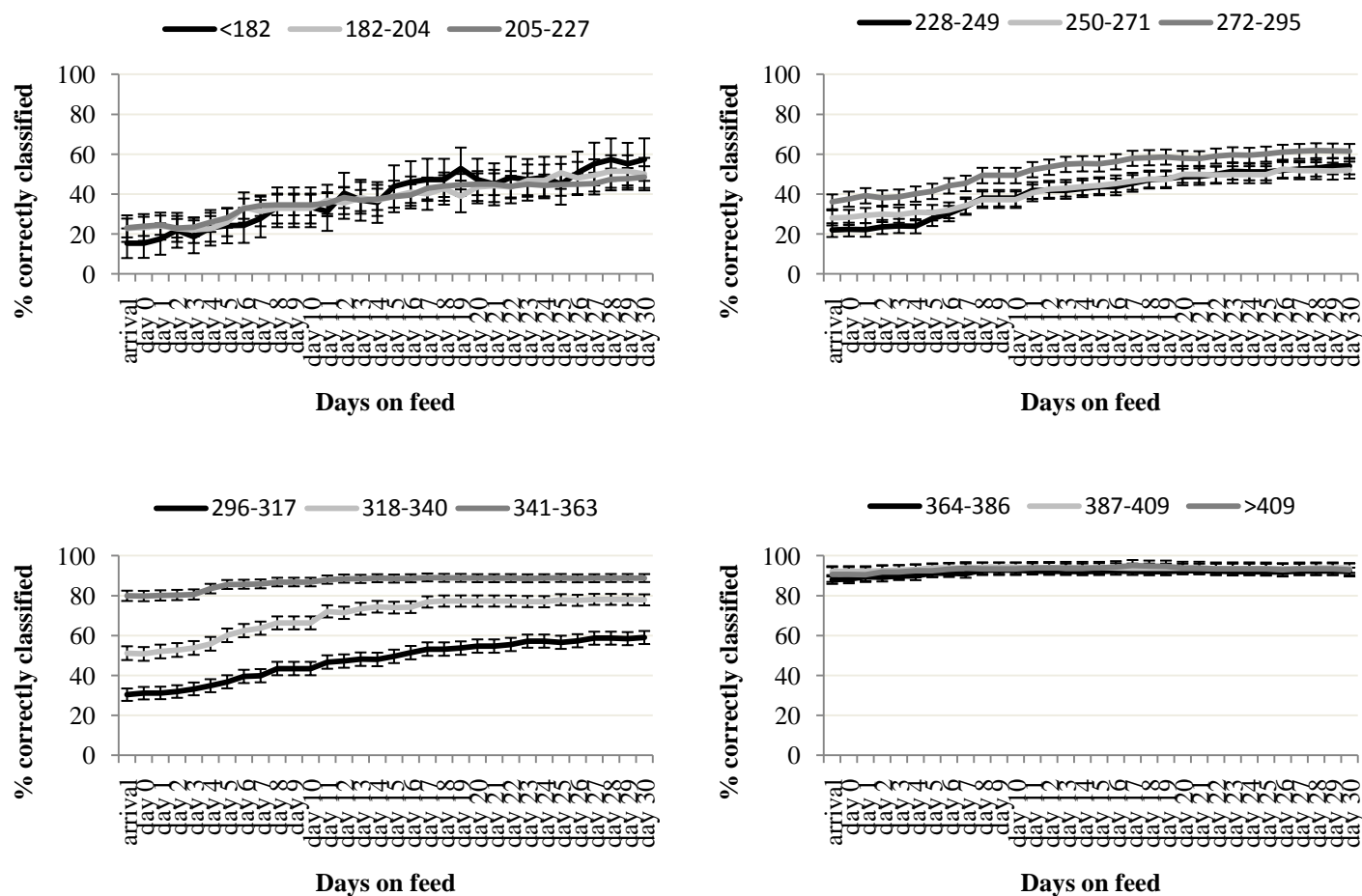
[a]Estimates from the final logistic generalized estimating equation, where lines represent the marginal means across days and arrival weights. Effects not displayed in the figure were included as a weighted average of the number of observations multiplied by the corresponding coefficient.

Figure 5.6 Model estimated[a] mean percent of cohorts where cumulative BRDC morbidity was correctly classified by model category[b] and day (subset 1 test data; n = 3,569) arriving to 20 U.S. feedlots from 2006 -2008. Error bars represent robust 95% confidence intervals.
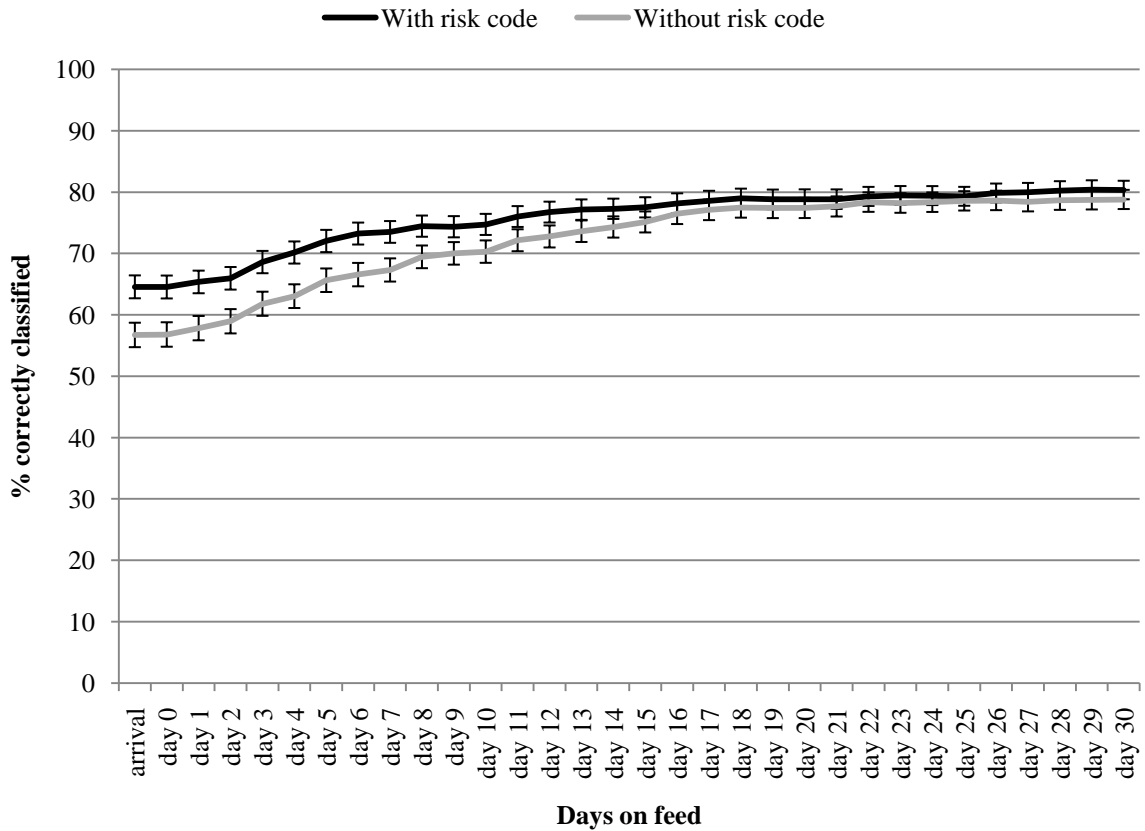
[a]Estimates from the final logistic generalized estimating equation, where lines represent the marginal means across days and model with and without risk code . Effects not displayed in the figure were included as a weighted average of the number of observations multiplied by the corresponding coefficient.
[b] Risk code was assigned to cohorts based on if they were "high" or "low" risk for BRDC following their standard protocols based on visual appraisal of animals at arrival, cattle source, transport time, and other factors.

Figure 5.7 Model estimated mean percent of cohorts where cumulative BRDC morbidity was correctly classified by model category[b] and day (subset 2 test data; n = 2,907) arriving to 20 U.S. feedlots from 2006 -2008. Error bars represent robust 95% confidence intervals.
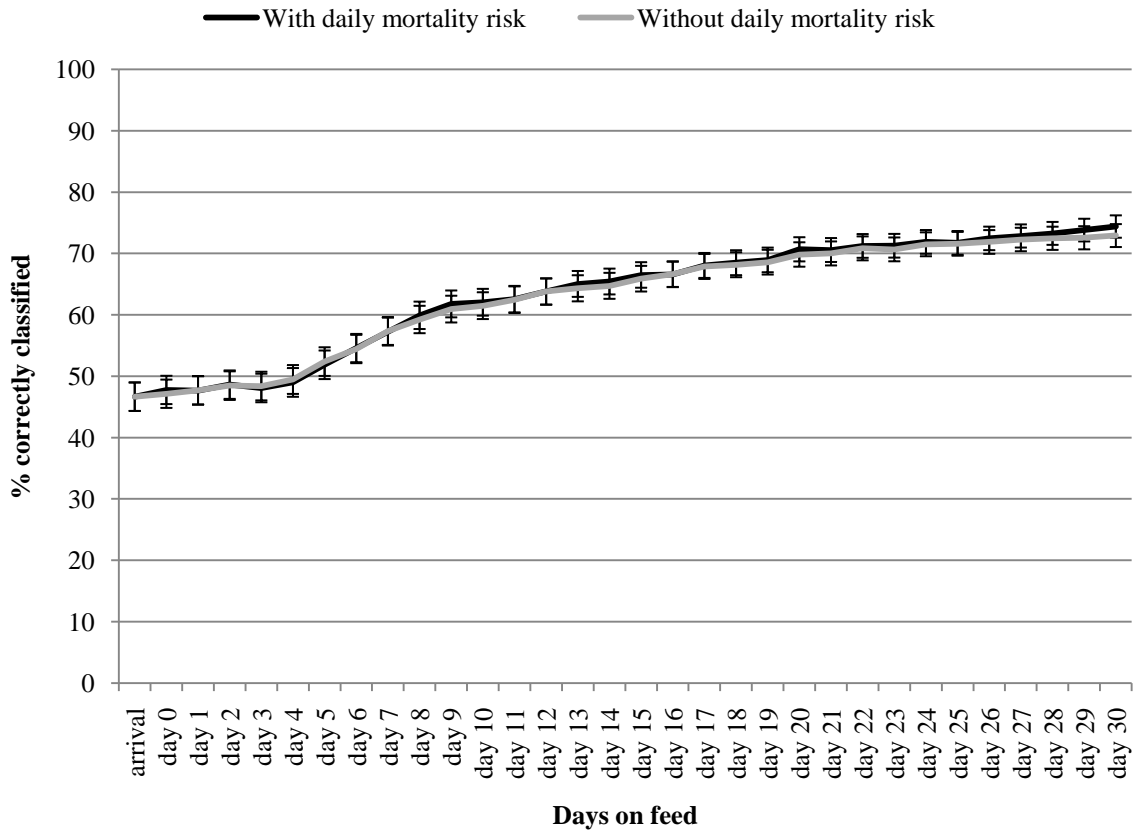
[a]Estimates from the final logistic generalized estimating equation, where lines represent the marginal means across days and model with and without mortality risk . Effects not displayed in the figure were included as a weighted average of the number of observations multiplied by the corresponding coefficient.
[b]Mortality risk is defined at the cohort level, as the number of animals that died divided by the number of animals that arrived to the feedlot (percent basis).

CHAPTER 6 - General Conclusions

Since "shipping fever" was first recognized as a serious post-weaning problem during the early 20th century, a large amount of research has focused on the etiology and pathogenesis of the disease. This research has yielded advances in biologicals and pharmaceuticals, yet has failed to eliminate or even reduce the health and economic impacts of BRDC. The epidemiology of BRDC in beef production systems in complex with multiple pathogen, host, and environmental interactions; these interactions result in variable disease expression. The role of risk factors and the timing of when BRDC cases occur have not been well quantified in the literature. One of the first and most comprehensive evaluations of the effect of risk factors for both BRDC morbidity and mortality was performed in Canada over 30 years ago. The impact of the timing of BRDC cases has just begun to be investigated over the past several years. Previous studies have indicated the need for a large scale epidemiological study quantifying both risk factors and the effect of the timing of BRDC cases in multiple commercial feedlots.

Technological advances have made the collection and utilization of large volumes of data possible in feedlots systems, and feedlots routinely collect cohort-level closeout data and daily animal health data, but quantitative information from these data are rarely available publicly. We were able to collect and verify feedlot data from 33 U.S. feedlots from six states over ten years. These data allowed us to utilize individual animal health records and cumulative cohort-level data to assess the temporal distributions and effects of the timing of BRDC cases, and to quantify the effects of risk factors and their interactions with regard to adverse health outcomes.

Feedlot veterinarians have stressed the importance of assessing the timing at which BRDC cases occur within a cohort, as these patterns may provide vital information regarding the identification and management of the syndrome. However, very little literature has described the effects of when BRDC cases occur, and none have identified distinct temporal patterns of disease that exist within feedlot cattle populations. In our first retrospective study utilizing unique individual animal data from one feedlot, we found that disease timing, when measured both relative to arrival and harvest, had substantial impacts on projected economic net returns. These data indicated that the

numbers of times cattle were treated and hot carcass weight were both largely affected by the time at which animals were first treated for BRDC relative to arrival. Cattle treated further from harvest had higher estimated net returns, which appeared to be related to increased hot carcass weights offsetting increased costs due to more treatments, longer days on feed, and decreased average daily gain. These results led us to believe that the timing of BRDC was important, and affected performance and health indices.

However, the individual animal performance data are not typical of the industry so we followed this study with one investigating BRDC timing effect on cohort (lot)-level outcomes. Through the use of cluster analysis we were able to identify seven distinct temporal patterns of BRDC at the cohort–level. These findings were the first to classify cumulative BRDC patterns among feedlot cohorts. Previous literature, largely based on anecdotal evidence, has suggested that temporal distributions may represent disease processes or cattle demographic factors that influence when cases of BRDC occur; perhaps also representing disease determinants that can be modified to mitigate BRDC. Our defined temporal patterns were associated with important performance and health indices, but it was difficult to broadly classify and summarize the associated effects as they were often modified across gender, weight, risk class, and cumulative morbidity categories. These results indicated that further research on the epidemiologic mechanisms related to temporal patterns of BRDC is needed, but that different temporal patterns exist and they may have important health and performance implications.

Research has suggested that multivariable approaches to assessing risk factors for feedlot health outcomes are important because cattle demographics are changing over time, both within and across feedlots; potentially confounding the observed relationships between seasonal patterns and health risks. With our large database we were able to quantify the effects of common risk factors for mortality and culling of feedlot cattle; outcomes that have a tremendous economic impact on North American feedlot production systems. The effect modification and potential for confounding that we observed, illustrate the importance of multivariable approaches when assessing data on heterogeneous feedlot cattle populations. Our results provided unique quantitative estimates for the effects of risk factors that have not been previously reported, and the

estimated effects from our analysis may be useful for feedlot risk managers assessing the costs of adverse health outcomes based on their available data.

Our previous studies utilized retrospective data to quantify the effects of the timing of BRDC cases, and risk factors on adverse health outcomes in commercial feedlots. The final project used similar statistical methods, but assessed the ability of these data to predict the cumulative BRDC risk within cohorts of feedlot cattle across days of the feeding period. To our knowledge, our study was the first to quantify the ability of multivariable statistical approaches at predicting cumulative BRDC using commercial feedlot animal health and cohort-level data. Our results demonstrated that the predictive performance of regression models can benefit from updated daily morbidity risk data, but the performance of the models was highly dependent of the demographics of the cohort. The results indicated that if more refined data regarding prior history of cohorts were collected on a consistent basis across feedlots we may be able to increase the predictive ability of models at cohort arrival, thus increasing the utility of such models in commercial feedlot settings.

With technological advances, it has become easy and inexpensive for feedlots to collect and store large amounts of data on cattle at arrival and during the feeding period. Our results indicate that these data could provide valuable information and that potentially powerful tools could be developed for feedlots if data are collected and organized in a fashion that is easy to access and analyze. From our work, it seems that the majority of feedlots have started to collect and store these data, but the industry lacks a standardized approach to doing so. To take full advantage of analytical approaches to epidemiologic and economic assessments, feedlots need to continue to collect more refined, consistent data throughout the beef production system. The use of the large feedlot database containing both individual animal health records and cumulative cohort-level data allowed for the quantification of the effects of the timing of BRDC cases in large commercial feedlots that had not been described in previous literature. In our investigations, the use of a large retrospective feedlot dataset allowed us to generate important quantitative measures of the effects of the timing of cases, effects of important arrival risk factors, and interaction effects that had been impossible to quantify with smaller scale feedlot studies.

170

Appendix A – Chapter 3 Full Tables

Table A.6.1 Final multivariable linear mixed model (with feedlot as a random effect[a]) for mean weight gain in kg/animal/day for feedlot cattle cohorts (n = 7,553)

Covariate	LR Test	Levels	b	S.E. (b)	95% CI	
Intercept			1.46	0.04	1.39	1.53
Temporal pattern	0.7932	1	Referent	0.00	0.00	0.00
		2	-0.04	0.02	-0.08	0.01
		3	-0.01	0.03	-0.06	0.04
		4	-0.01	0.04	-0.08	0.07
		5	-0.01	0.03	-0.07	0.05
		6	-0.01	0.03	-0.06	0.04
		7	0.00	0.03	-0.06	0.06
Gender	<0.0001	Male	Referent	0.00	0.00	0.00
		Female	-0.12	0.00	-0.13	-0.11
Arrival weight (kg)	<0.0001	>409	Referent	0.00	0.00	0.00
		363-408	-0.04	0.02	-0.08	0.00
		318-362	-0.05	0.02	-0.09	-0.01
		272-317	-0.10	0.02	-0.14	-0.07
		227-271	-0.19	0.02	-0.22	-0.15
		182-226	-0.29	0.02	-0.33	-0.25
		<182	-0.33	0.03	-0.39	-0.28
Cumulative morbidity	<0.0001	0-<5%	0.00	0.00	0.00	0.00
		5-<10%	0.02	0.00	0.01	0.03
		10-<20%	0.02	0.00	0.01	0.03
		≥ 20%	0.01	0.01	-0.01	0.02
Risk Code	0.9518	Low	Referent	0.00	0.00	0.00
		High	0.00	0.01	-0.02	0.02
Temporal pattern X	0.0212	1 X ≥ 409	Referent			
Arrival weight		1 X 363-408	Referent			
		1 X 318-362	Referent			
		1 X 272-317	Referent			
		1 X 227-271	Referent			
		1 X 182-226	Referent			
		1 X <182	Referent			
		2 X ≥ 409	Referent			
		2 X 363-408	0.03	0.03	-0.02	0.08
		2 X 318-362	0.03	0.03	-0.02	0.08
		2 X 272-317	0.03	0.02	-0.02	0.08
		2 X 227-271	0.04	0.03	-0.01	0.09

171

		2 X 182-226	0.07	0.03	0.01	0.12
		2 X <182	0.07	0.04	0.00	0.15
		3 X ≥ 409	Referent			
		3 X 363-408	0.02	0.03	-0.03	0.08
		3 X 318-362	-0.01	0.03	-0.06	0.05
		3 X 272-317	0.04	0.03	-0.03	0.08
		3 X 227-271	0.03	0.03	-0.03	0.08
		3 X 182-226	0.01	0.03	0.01	0.13
		3 X <182	-0.02	0.05	-0.11	0.07
		4 X ≥ 409	Referent			
		4 X 363-408	0.03	0.04	-0.05	0.11
		4 X 318-362	0.00	0.04	-0.08	0.08
		4 X 272-317	0.01	0.04	-0.07	0.09
		4 X 227-271	0.01	0.04	-0.08	0.09
		4 X 182-226	0.09	0.05	0.00	0.18
		4 X <182	0.01	0.06	-0.11	0.14
		5 X ≥ 409	Referent			
		5 X 363-408	0.03	0.03	-0.03	0.10
		5 X 318-362	0.02	0.03	-0.04	0.07
		5 X 272-317	0.02	0.03	-0.04	0.08
		5 X 227-271	0.01	0.03	-0.05	0.07
		5 X 182-226	0.05	0.03	-0.02	0.12
		5 X <182	0.09	0.06	-0.02	0.20
		6 X ≥ 409	Referent			
		6 X 363-408	0.02	0.03	-0.04	0.07
		6 X 318-362	0.02	0.03	-0.04	0.07
		6 X 272-317	0.04	0.03	-0.02	0.09
		6 X 227-271	0.01	0.03	-0.05	0.07
		6 X 182-226	0.05	0.04	-0.02	0.12
		6 X <182	0.00	0.08	-0.16	0.15
		7 X ≥ 409	Referent			
		7 X 363-408	0.03	0.03	-0.04	0.10
		7 X 318-362	0.04	0.03	-0.03	0.10
		7 X 272-317	0.02	0.03	-0.05	0.09
		7 X 227-271	0.00	0.04	-0.07	0.08
		7 X 182-226	-0.06	0.05	-0.17	0.04
		7 X <182	0.00	0.08	-0.16	0.16
Temporal pattern X Risk Code	0.0137	1 X Low	Referent			
		2 X Low	Referent			
		3 X Low	Referent			
		4 X Low	Referent			
		5 X Low	Referent			

172

		6 X Low	Referent			
		7 X Low	Referent			
		1 X High	Referent			
		2 X High	-0.02	0.01	-0.05	0.00
		3 X High	-0.04	0.01	-0.07	-0.02
		4 X High	-0.04	0.02	-0.07	0.00
		5 X High	-0.04	0.01	-0.07	-0.01
		6 X High	-0.04	0.02	-0.07	-0.01
		7 X High	-0.02	0.03	-0.08	0.03
Time	<0.0001	1	Referent			
		2	0.01	0.03	-0.05	0.07
		3	0.04	0.03	-0.02	0.10
		4	0.04	0.03	-0.02	0.10
		5	0.00	0.03	-0.06	0.06
		6	-0.03	0.03	-0.09	0.03
		7	-0.02	0.03	-0.08	0.04
		8	0.03	0.03	-0.03	0.09
		9	0.07	0.03	0.01	0.13
		10	0.03	0.03	-0.03	0.10
		11	0.04	0.03	-0.02	0.10
		12	0.05	0.03	-0.01	0.11
		13	0.02	0.03	-0.04	0.08
		14	0.02	0.03	-0.04	0.08
		15	-0.02	0.03	-0.08	0.04
		16	-0.04	0.03	-0.10	0.02
		17	-0.07	0.03	-0.13	-0.01
		18	-0.08	0.03	-0.14	-0.02
		19	-0.06	0.03	-0.12	0.00
		20	0.00	0.03	-0.06	0.06
		21	0.10	0.03	0.04	0.16
		22	0.11	0.03	0.05	0.17
		23	0.12	0.03	0.06	0.18
		24	0.10	0.03	0.04	0.16
		25	0.07	0.03	0.01	0.12
		26	0.07	0.03	0.01	0.13
		27	0.04	0.03	-0.02	0.10
		28	0.02	0.03	-0.04	0.08
		29	0.00	0.03	-0.06	0.06
		30	-0.01	0.03	-0.07	0.05
		31	-0.02	0.03	-0.08	0.04
		32	0.02	0.03	-0.04	0.08
		33	0.12	0.03	0.06	0.18

34	0.15	0.03	0.09	0.21
35	0.19	0.03	0.13	0.25
36	0.19	0.04	0.11	0.26
37	0.12	0.13	-0.13	0.37

[a]Random effect for feedlot ($P < 0.01$); 8.6 percent of the variance came from between feedlots and 91.4 percent within feedlots

Table A.6.2 Final multivariable linear mixed model (with feedlot as a random effect[a]) for mean days on feed for feedlot cattle cohorts (n = 7,553)

Covariate	LR Test	Levels	b	S.E. (b)	95% CI	
Intercept			128.79	4.82	119.35	138.22
Temporal pattern	0.4228	1	Referent			
		2	1.97	3.27	-4.44	8.38
		3	8.07	3.56	1.09	15.04
		4	1.71	5.22	-8.51	11.94
		5	4.44	3.98	-3.36	12.25
		6	2.26	3.65	-4.90	9.42
		7	4.48	4.27	-3.88	12.84
Gender	<0.0001	Male	Referent			
		Female	-29.27	0.46	-30.18	-28.37
Arrival weight (kg)	<0.0001	>409	Referent			
		363-408	25.08	2.67	19.84	30.31
		318-362	46.11	2.53	41.16	51.06
		272-317	73.23	2.48	68.38	78.09
		227-271	109.05	2.59	103.98	114.12
		182-226	150.30	2.90	144.62	155.97
		<182	206.17	3.92	198.49	213.86
Cumulative morbidity	0.0121	0-<5%	Referent			
		5-<10%	-0.21	0.55	-1.29	0.88
		10-<20%	1.63	0.67	0.33	2.94
		≥ 20%	1.90	0.79	0.36	3.45
Risk code	<0.0001	Low	Referent			
		High	7.22	1.17	4.93	9.52
Temporal pattern X Arrival weight	<0.0001	1 X ≥ 409	Referent			
		1 X 363-408	Referent			
		1 X 318-362	Referent			
		1 X 272-317	Referent			
		1 X 227-271	Referent			
		1 X 182-226	Referent			
		1 X <182	Referent			
		2 X ≥ 409	Referent			
		2 X 363-408	-1.42	3.62	-8.52	5.68
		2 X 318-362	-0.27	3.42	-6.98	6.44
		2 X 272-317	-2.76	3.37	-9.37	3.84
		2 X 227-271	0.91	3.48	-5.92	7.73
		2 X 182-226	-5.50	3.79	-12.93	1.93
		2 X <182	-13.31	5.27	-23.64	-2.99
		3 X ≥ 409	Referent			

		3 X 363-408	-8.98	3.87	-16.57	-1.39
		3 X 318-362	-6.94	3.70	-14.19	0.32
		3 X 272-317	-9.36	3.71	-16.63	-2.10
		3 X 227-271	-7.16	3.88	-14.77	0.45
		3 X 182-226	-11.72	4.30	-20.15	-3.29
		3 X <182	-9.28	6.38	-21.77	3.22
		4 X ≥ 409	Referent			
		4 X 363-408	-1.75	5.60	-12.74	9.23
		4 X 318-362	0.10	5.40	-10.48	10.69
		4 X 272-317	-2.15	5.42	-12.76	8.46
		4 X 227-271	-3.33	5.65	-14.41	7.76
		4 X 182-226	-17.00	6.22	-29.20	-4.81
		4 X <182	-9.59	8.81	-26.85	7.67
		5 X ≥ 409	Referent			
		5 X 363-408	-5.20	4.26	-13.56	3.16
		5 X 318-362	-3.52	4.12	-11.59	4.55
		5 X 272-317	-5.72	4.10	-13.77	2.32
		5 X 227-271	-2.78	4.28	-11.17	5.61
		5 X 182-226	-5.28	4.73	-14.55	3.98
		5 X <182	-28.21	7.73	-43.35	-13.06
		6 X ≥ 409	Referent			
		6 X 363-408	-1.37	4.00	-9.22	6.47
		6 X 318-362	-2.46	3.83	-9.97	5.05
		6 X 272-317	-2.92	3.92	-10.61	4.77
		6 X 227-271	-2.55	4.16	-10.70	5.61
		6 X 182-226	5.62	4.81	-3.80	15.05
		6 X <182	-26.49	10.81	-47.68	-5.31
		7 X ≥ 409	Referent			
		7 X 363-408	-6.66	4.72	-15.91	2.59
		7 X 318-362	-6.97	4.56	-15.92	1.97
		7 X 272-317	-9.37	4.71	-18.60	-0.13
		7 X 227-271	-6.33	5.01	-16.15	3.49
		7 X 182-226	11.84	7.08	-2.03	25.72
		7 X <182	23.07	11.18	1.15	44.98
Temporal pattern X Risk code	0.001	1 X Low	Referent			
		2 X Low	Referent			
		3 X Low	Referent			
		4 X Low	Referent			
		5 X Low	Referent			
		6 X Low	Referent			
		7 X Low	Referent			
		1 X High	Referent			

		2 X High	2.51	1.52	-0.47	5.48
		3 X High	6.02	1.69	2.71	9.34
		4 X High	4.58	2.29	0.08	9.08
		5 X High	2.70	1.77	-0.77	6.18
		6 X High	7.52	2.20	3.21	11.83
		7 X High	-3.41	3.87	-11.00	4.18
Time	<0.0001	1	Referent			
		2	-12.89	4.47	-21.65	-4.13
		3	-4.30	4.23	-12.58	3.99
		4	-0.79	4.19	-9.00	7.42
		5	0.94	4.11	-7.12	8.99
		6	6.34	4.09	-1.68	14.35
		7	6.55	4.13	-1.54	14.65
		8	0.31	4.23	-7.97	8.60
		9	-3.42	4.14	-11.54	4.70
		10	-4.54	4.29	-12.94	3.86
		11	-4.21	4.18	-12.40	3.98
		12	-5.21	4.33	-13.70	3.29
		13	-1.86	4.18	-10.04	6.33
		14	-3.32	4.17	-11.49	4.85
		15	0.70	4.11	-7.36	8.76
		16	3.97	4.10	-4.06	12.00
		17	10.44	4.10	2.41	18.47
		18	9.23	4.10	1.19	17.27
		19	15.39	4.16	7.24	23.54
		20	8.76	4.17	0.58	16.94
		21	-3.82	4.10	-11.85	4.22
		22	-2.83	4.15	-10.97	5.30
		23	-4.60	4.09	-12.61	3.41
		24	-8.32	4.19	-16.52	-0.11
		25	-3.62	4.04	-11.54	4.30
		26	-2.40	4.10	-10.43	5.63
		27	-2.53	4.08	-10.53	5.47
		28	1.43	4.06	-6.52	9.37
		29	4.38	4.04	-3.53	12.29
		30	0.81	4.05	-7.13	8.74
		31	0.16	4.09	-7.86	8.17
		32	-2.64	4.16	-10.78	5.51
		33	-5.06	4.13	-13.16	3.03
		34	-5.01	4.09	-13.03	3.01
		35	-8.75	4.24	-17.07	-0.43
		36	-8.87	5.35	-19.37	1.62

| | 37 | -20.11 | 17.33 | -54.07 | 13.85 |

[a]Random effect for feedlot ($P < 0.01$); 5.1 percent of the variance came from between feedlots and 94.9 percent within feedlots

Table A.6.3 Final multivariable linear mixed model (with feedlot as a random effect[a]) for mean carcass weight in kg for feedlot cattle cohorts (n = 7,447)

Covariate	LR Test	Levels	b	S.E. (b)	95% CI	
Intercept			391.83	30.22	332.60	451.06
Temporal pattern	0.0489	1	Referent			
		2	-12.81	20.68	-53.34	27.71
		3	40.10	22.31	-3.62	83.82
		4	-7.48	32.71	-71.60	56.63
		5	-21.31	24.97	-70.25	27.64
		6	-5.31	22.91	-50.22	39.60
		7	49.75	26.75	-2.68	102.18
Gender	<0.0001	Male	Referent			
		Female	-51.17	2.92	-56.89	-45.46
Arrival weight (kg)	<0.0001	>409	Referent			
		363-408	-31.63	16.77	-64.51	1.24
		318-362	-27.70	15.85	-58.76	3.36
		272-317	-27.48	15.53	-57.92	2.96
		227-271	-73.00	16.27	-104.88	-41.12
		182-226	-89.05	18.38	-125.08	-53.03
		<182	-87.47	24.58	-135.66	-39.29
Cumulative morbidity	0.005	0-<5%	Referent			
		5-<10%	10.55	3.48	3.73	17.36
		10-<20%	11.23	4.21	2.98	19.48
		≥ 20%	10.77	4.98	1.02	20.53
Risk code	<0.0001	Low	Referent			
		High	56.80	7.38	42.34	71.27
Temporal pattern X	<0.0001	1 X ≥ 409	Referent			
Arrival weight		1 X 363-408	Referent			
		1 X 318-362	Referent			
		1 X 272-317	Referent			
		1 X 227-271	Referent			
		1 X 182-226	Referent			
		1 X <182	Referent			
		2 X ≥ 409	Referent			
		2 X 363-408	16.52	22.86	-28.29	61.33
		2 X 318-362	0.10	21.63	-42.29	42.48
		2 X 272-317	-12.73	21.28	-54.44	28.97
		2 X 227-271	26.47	22.03	-16.71	69.65
		2 X 182-226	11.04	24.11	-36.22	58.30
		2 X <182	34.49	33.27	-30.71	99.69
		3 X ≥ 409	Referent			
		3 X 363-408	-37.19	24.30	-84.81	10.44

179

		3 X 318-362	-36.99	23.22	-82.50	8.52
		3 X 272-317	-51.27	23.25	-96.83	-5.71
		3 X 227-271	-34.41	24.40	-82.23	13.41
		3 X 182-226	-7.34	27.21	-60.67	45.99
		3 X <182	14.66	39.98	-63.70	93.02
		4 X ≥ 409	Referent			
		4 X 363-408	16.37	35.15	-52.52	85.26
		4 X 318-362	0.20	33.88	-66.21	66.60
		4 X 272-317	-7.88	33.97	-74.46	58.69
		4 X 227-271	35.51	35.48	-34.04	105.05
		4 X 182-226	57.48	39.36	-19.66	134.62
		4 X <182	1.28	55.22	-106.96	109.51
		5 X ≥ 409	Referent			
		5 X 363-408	32.53	26.75	-19.90	84.96
		5 X 318-362	16.08	25.82	-34.53	66.69
		5 X 272-317	7.16	25.74	-43.30	57.62
		5 X 227-271	48.89	26.90	-3.84	101.62
		5 X 182-226	44.36	29.80	-14.05	102.77
		5 X <182	77.59	48.46	-17.39	172.56
		6 X ≥ 409	Referent			
		6 X 363-408	16.16	25.12	-33.07	65.39
		6 X 318-362	-3.08	24.05	-50.22	44.05
		6 X 272-317	-22.39	24.60	-70.61	25.82
		6 X 227-271	21.11	26.14	-30.13	72.35
		6 X 182-226	71.24	30.30	11.85	130.63
		6 X <182	-29.21	67.80	-162.09	103.67
		7 X ≥ 409	Referent			
		7 X 363-408	-46.32	29.61	-104.35	11.71
		7 X 318-362	-43.76	28.62	-99.85	12.33
		7 X 272-317	-73.17	29.61	-131.20	-15.14
		7 X 227-271	14.32	31.45	-47.32	75.96
		7 X 182-226	25.69	44.50	-61.52	112.91
		7 X <182	95.74	70.17	-41.80	233.27
Pattern X	<0.0001	1 X Low	Referent			
Risk code		2 X Low	Referent			
		3 X Low	Referent			
		4 X Low	Referent			
		5 X Low	Referent			
		6 X Low	Referent			
		7 X Low	Referent			
		1 X High	Referent			
		2 X High	-26.32	9.60	-45.13	-7.51

		3 X High	-28.64	10.69	-49.60	-7.68
		4 X High	-46.26	14.52	-74.72	-17.80
		5 X High	-51.04	11.21	-73.02	-29.06
		6 X High	-5.99	13.93	-33.30	21.32
		7 X High	-84.13	24.78	-132.71	-35.56
Time	<0.0001	1	Referent			
		2	-5.70	28.02	-60.62	49.21
		3	22.68	26.51	-29.28	74.64
		4	35.62	26.28	-15.88	87.13
		5	27.46	25.77	-23.05	77.96
		6	22.94	25.67	-27.37	73.25
		7	27.39	25.91	-23.39	78.18
		8	9.42	26.52	-42.55	61.39
		9	35.56	25.99	-15.38	86.50
		10	37.92	26.88	-14.75	90.60
		11	31.26	26.22	-20.12	82.64
		12	44.83	27.19	-8.45	98.12
		13	43.12	26.24	-8.31	94.54
		14	28.71	26.19	-22.62	80.05
		15	18.93	25.81	-31.65	69.52
		16	13.36	25.70	-37.02	63.74
		17	45.41	25.70	-4.95	95.77
		18	42.65	25.74	-7.80	93.10
		19	38.71	26.12	-12.49	89.90
		20	61.87	26.18	10.56	113.18
		21	46.88	25.72	-3.54	97.29
		22	58.37	26.03	7.36	109.39
		23	65.04	25.64	14.79	115.30
		24	40.95	26.29	-10.58	92.47
		25	41.48	25.36	-8.23	91.19
		26	59.30	25.70	8.92	109.68
		27	41.38	25.62	-8.83	91.59
		28	62.57	25.44	12.71	112.43
		29	68.84	25.33	19.19	118.49
		30	66.44	25.39	16.67	116.21
		31	53.92	25.66	3.62	104.22
		32	42.35	26.11	-8.83	93.53
		33	54.37	25.92	3.57	105.18
		34	60.61	25.67	10.29	110.93
		35	49.19	26.62	-2.97	101.36
		36	41.48	33.58	-24.34	107.30
		37	54.00	108.64	-158.93	266.93

Table A.6.4 Final multivariable logistic regression model[a] of the probability of USDA Yield Grade One or Two carcasses within feedlot cattle cohorts (n = 7,447)

Covariate	$P > \chi^2$	Level	b	Robust S.E. (b)	OR	95% CI OR	
Intercept			0.91	0.11			
Temporal pattern	<0.0001	1	Referent				
		2	0.04	0.02	1.04	0.99	1.09
		3	-0.04	0.03	0.96	0.91	1.01
		4	-0.02	0.03	0.98	0.93	1.04
		5	-0.05	0.03	0.95	0.91	1.00
		6	-0.13	0.03	0.88	0.83	0.93
		7	-0.10	0.04	0.91	0.84	0.98
Gender	<0.0001	Male	Referent				
		Female	-0.25	0.03	0.78	0.73	0.83
Arrival weight (kg)	<0.0001	>409	Referent				
		363-408	-0.24	0.07	0.79	0.73	0.86
		318-362	-0.23	0.05	0.79	0.73	0.86
		272-317	-0.24	0.04	0.79	0.73	0.85
		227-271	-0.27	0.04	0.76	0.70	0.83
		182-226	-0.24	0.04	0.79	0.72	0.87
		<182	-0.28	0.04	0.75	0.65	0.87
Cumulative morbidity	0.7578	0-<5%	Referent				
		5-<10%	-0.01	0.02	0.99	0.96	1.03
		10-<20%	-0.02	0.02	0.98	0.94	1.03
		≥ 20%	0.01	0.03	1.01	0.96	1.06
Risk code	0.00290	Low	Referent				
		High	-0.06	0.02	0.94	0.90	0.98
Temporal pattern X Gender	<0.0001	1 X Male					
		2 X Male					
		3 X Male					
		4 X Male					
		5 X Male					
		6 X Male					
		7 X Male					
		1 X Female					
		2 X Female	-0.11	0.04	0.90	0.83	0.98
		3 X Female	-0.11	0.05	0.90	0.82	0.99
		4 X Female	0.02	0.06	1.02	0.90	1.16
		5 X Female	0.04	0.05	1.04	0.95	1.15
		6 X Female	0.15	0.05	1.16	1.05	1.29
		7 X Female	0.01	0.08	1.01	0.87	1.18

Time	<0.0001	1	Referent			
		2	0.06	0.11	1.06	0.85 1.33
		3	-0.01	0.11	0.99	0.80 1.21
		4	0.02	0.10	1.02	0.84 1.25
		5	0.08	0.10	1.08	0.88 1.32
		6	0.17	0.10	1.18	0.97 1.45
		7	0.09	0.10	1.09	0.89 1.34
		8	0.08	0.11	1.09	0.88 1.34
		9	0.08	0.10	1.08	0.88 1.33
		10	0.07	0.11	1.08	0.87 1.34
		11	-0.07	0.10	0.94	0.76 1.15
		12	-0.01	0.11	0.99	0.79 1.23
		13	0.07	0.11	1.07	0.87 1.32
		14	0.17	0.11	1.19	0.97 1.46
		15	0.12	0.10	1.13	0.92 1.39
		16	0.15	0.10	1.16	0.94 1.41
		17	0.14	0.10	1.15	0.94 1.41
		18	0.26	0.11	1.30	1.06 1.59
		19	0.22	0.11	1.25	1.01 1.54
		20	0.08	0.11	1.08	0.87 1.34
		21	-0.15	0.10	0.86	0.70 1.05
		22	-0.13	0.10	0.88	0.71 1.08
		23	-0.14	0.10	0.87	0.71 1.07
		24	0.03	0.11	1.03	0.84 1.28
		25	0.01	0.10	1.01	0.83 1.23
		26	0.08	0.10	1.08	0.88 1.32
		27	0.17	0.10	1.18	0.97 1.45
		28	0.24	0.10	1.27	1.04 1.55
		29	0.23	0.10	1.26	1.04 1.54
		30	0.43	0.10	1.53	1.25 1.87
		31	0.54	0.10	1.71	1.40 2.10
		32	0.57	0.11	1.76	1.42 2.18
		33	0.23	0.11	1.26	1.03 1.56
		34	0.08	0.10	1.08	0.88 1.32
		35	0.06	0.11	1.06	0.86 1.31
		36	-0.08	0.14	0.92	0.71 1.21
		37	-0.74	0.11	0.48	0.39 0.59
Feedlot	<0.0001	1	Referent			
		2	-0.48	0.02	0.62	0.59 0.65
		3	0.27	0.03	1.31	1.24 1.39
		4	-0.09	0.03	0.92	0.87 0.97
		5	-0.57	0.05	0.57	0.52 0.62

184

6	-0.86	0.03	0.42	0.40	0.45
7	0.01	0.03	1.01	0.96	1.07
8	0.26	0.03	1.30	1.24	1.37
9	-0.82	0.04	0.44	0.41	0.47

[a]Model was estimated using a generalized estimating equation with cohort as a panel variable and a exchangeable correlation structure

Table A.6.5 Final multivariable logistic regression model[a] of the probability of USDA Quality Grade Choice or Prime carcasses within feedlot cattle cohorts (n = 7,447 cohorts)

Covariate	$P > \chi 2$	Level	b	Robust S.E. (b)	OR	95% CI OR	
Intercept			-0.92	0.16			
Temporal pattern	0.0165	1	Referent				
		2	-0.15	0.14	0.86	0.65	1.14
		3	0.20	0.14	1.23	0.93	1.61
		4	0.41	0.16	1.50	1.09	2.06
		5	0.02	0.14	1.02	0.77	1.34
		6	0.11	0.13	1.12	0.86	1.45
		7	0.28	0.14	1.33	1.01	1.74
Gender	<0.0001	Male	Referent				
		Female	0.40	0.02	1.49	1.44	1.53
Arrival weight (kg)	<0.0001	>409	Referent				
		363-408	0.39	0.09	1.47	1.22	1.77
		318-362	0.48	0.09	1.61	1.35	1.93
		272-317	0.61	0.09	1.84	1.55	2.19
		227-271	0.77	0.09	2.15	1.79	2.59
		182-226	1.15	0.12	3.15	2.50	3.96
		<182	1.09	0.12	2.98	2.35	3.79
Cumulative morbidity	<0.0001	0-<5%	Referent				
		5-<10%	-0.18	0.04	0.84	0.77	0.91
		10-<20%	-0.26	0.04	0.77	0.71	0.84
		$\geq 20\%$	-0.45	0.05	0.64	0.58	0.70
Risk code	<0.0001	Low	Referent				
		High	-0.15	0.04	0.86	0.80	0.93
Temporal pattern X Arrival weight	<0.0001	1 X ≥ 409	Referent				
		1 X 363-408	Referent				
		1 X 318-362	Referent				
		1 X 272-317	Referent				
		1 X 227-271	Referent				
		1 X 182-226	Referent				
		1 X <182	Referent				
		2 X ≥ 409	Referent				
		2 X 363-408	0.10	0.15	1.11	0.83	1.49
		2 X 318-362	0.06	0.15	1.06	0.80	1.41
		2 X 272-317	0.07	0.14	1.07	0.81	1.42
		2 X 227-271	-0.01	0.15	0.99	0.74	1.33
		2 X 182-226	-0.23	0.17	0.80	0.57	1.11
		2 X <182	0.10	0.19	1.10	0.76	1.60

		3 X ≥ 409	Referent			
		3 X 363-408	-0.25	0.15	0.78	0.59	1.04
		3 X 318-362	-0.29	0.14	0.75	0.57	0.99
		3 X 272-317	-0.26	0.14	0.77	0.58	1.02
		3 X 227-271	-0.17	0.15	0.84	0.63	1.13
		3 X 182-226	-0.36	0.18	0.70	0.50	0.99
		3 X <182	-0.24	0.18	0.79	0.55	1.12
		4 X ≥ 409	Referent			
		4 X 363-408	-0.52	0.17	0.59	0.43	0.83
		4 X 318-362	-0.53	0.17	0.59	0.43	0.82
		4 X 272-317	-0.59	0.17	0.55	0.40	0.77
		4 X 227-271	-0.67	0.17	0.51	0.36	0.72
		4 X 182-226	-0.90	0.22	0.41	0.26	0.62
		4 X <182	-1.01	0.25	0.37	0.22	0.60
		5 X ≥ 409	Referent			
		5 X 363-408	-0.15	0.15	0.86	0.65	1.14
		5 X 318-362	-0.14	0.14	0.87	0.66	1.15
		5 X 272-317	-0.08	0.14	0.93	0.70	1.23
		5 X 227-271	0.02	0.15	1.02	0.76	1.37
		5 X 182-226	-0.34	0.18	0.71	0.50	1.00
		5 X <182	-0.58	0.25	0.56	0.34	0.92
		6 X ≥ 409	Referent			
		6 X 363-408	-0.16	0.14	0.85	0.64	1.12
		6 X 318-362	-0.12	0.14	0.89	0.68	1.16
		6 X 272-317	-0.22	0.14	0.80	0.61	1.06
		6 X 227-271	-0.16	0.15	0.85	0.64	1.15
		6 X 182-226	-0.54	0.18	0.58	0.41	0.83
		6 X <182	-0.31	0.23	0.73	0.46	1.16
		7 X ≥ 409	Referent			
		7 X 363-408	-0.30	0.15	0.74	0.55	0.99
		7 X 318-362	-0.20	0.15	0.82	0.61	1.09
		7 X 272-317	-0.16	0.15	0.85	0.64	1.14
		7 X 227-271	-0.44	0.16	0.65	0.47	0.89
		7 X 182-226	-0.62	0.26	0.54	0.32	0.91
		7 X <182	-0.61	0.43	0.54	0.23	1.27
[b]Temporal pattern X Cumulative morbidity	0.0175	1 X 0-<5%	Referent			
		1 X 5-<10%	Referent			
		1 X 10-<20%	Referent			
		1 X ≥ 20%	Referent			
		2 X 0-<5%	Referent			
		2 X 5-<10%	0.07	0.06	1.07	0.96	1.20
		2 X 10-<20%	0.16	0.06	1.17	1.04	1.31

		2 X ≥ 20%	0.10	0.07	1.10	0.96	1.26
		3 X 0-<5%	Referent				
		3 X 5-<10%	0.11	0.06	1.11	0.99	1.25
		3 X 10-<20%	0.02	0.07	1.02	0.89	1.17
		3 X ≥ 20%	0.19	0.08	1.20	1.03	1.41
		4 X 0-<5%	Referent				
		4 X 5-<10%	0.09	0.07	1.09	0.96	1.25
		4 X 10-<20%	0.19	0.08	1.20	1.03	1.41
		4 X ≥ 20%	0.14	0.11	1.15	0.93	1.42
		5 X 0-<5%	Referent				
		5 X 5-<10%	0.10	0.06	1.10	0.99	1.23
		5 X 10-<20%	0.06	0.07	1.06	0.92	1.22
		5 X ≥ 20%	0.00	0.11	1.00	0.80	1.26
		6 X 0-<5%	Referent				
		6 X 5-<10%	0.01	0.07	1.01	0.88	1.17
		6 X 10-<20%	-0.02	0.11	0.98	0.79	1.20
		6 X ≥ 20%	0.42	0.18	1.52	1.06	2.18
		7 X 0-<5%	Referent				
		7 X 5-<10%	0.85	0.44	2.35	0.99	5.56
		7 X 10-<20%	N/A[b]				
		7 X ≥ 20%	N/A[b]				
Temporal pattern X Risk code	0.0152	1 X Low	Referent				
		2 X Low	Referent				
		3 X Low	Referent				
		4 X Low	Referent				
		5 X Low	Referent				
		6 X Low	Referent				
		7 X Low	Referent				
		1 X High	Referent				
		2 X High	0.07	0.06	1.08	0.96	1.21
		3 X High	0.03	0.07	1.03	0.91	1.18
		4 X High	0.22	0.08	1.24	1.06	1.46
		5 X High	0.13	0.07	1.14	1.00	1.29
		6 X High	0.21	0.08	1.24	1.05	1.46
		7 X High	0.31	0.14	1.37	1.05	1.78
Time	<0.0001	1	Referent				
		2	0.05	0.14	1.05	0.79	1.39
		3	0.08	0.14	1.08	0.83	1.41
		4	0.13	0.14	1.14	0.87	1.49
		5	0.15	0.14	1.17	0.90	1.52
		6	0.17	0.14	1.19	0.91	1.55
		7	0.09	0.14	1.10	0.84	1.43

188

		8	0.04	0.14	1.04	0.79	1.37
		9	-0.12	0.14	0.89	0.68	1.16
		10	-0.04	0.14	0.96	0.73	1.26
		11	0.04	0.14	1.04	0.79	1.36
		12	0.03	0.14	1.03	0.78	1.37
		13	0.14	0.14	1.15	0.87	1.50
		14	0.08	0.14	1.09	0.83	1.43
		15	-0.09	0.14	0.91	0.70	1.19
		16	0.14	0.13	1.16	0.89	1.50
		17	0.14	0.13	1.15	0.88	1.49
		18	0.16	0.14	1.17	0.90	1.53
		19	0.18	0.14	1.19	0.91	1.56
		20	0.17	0.14	1.18	0.90	1.55
		21	0.35	0.13	1.42	1.09	1.85
		22	0.15	0.14	1.16	0.89	1.51
		23	0.27	0.13	1.30	1.00	1.70
		24	0.07	0.14	1.07	0.81	1.41
		25	0.02	0.13	1.02	0.79	1.33
		26	0.03	0.14	1.03	0.79	1.35
		27	0.07	0.13	1.07	0.83	1.40
		28	0.14	0.13	1.15	0.89	1.50
		29	0.21	0.13	1.23	0.95	1.61
		30	0.05	0.13	1.05	0.81	1.36
		31	-0.04	0.14	0.96	0.73	1.26
		32	-0.06	0.14	0.94	0.72	1.25
		33	0.09	0.14	1.10	0.84	1.43
		34	0.12	0.13	1.13	0.87	1.47
		35	0.05	0.14	1.05	0.81	1.38
		36	-0.05	0.16	0.95	0.69	1.30
		37	0.15	0.17	1.16	0.83	1.62
Feedlot	<0.0001	1	Referent				
		2	0.14	0.02	1.15	1.10	1.20
		3	0.00	0.03	1.00	0.95	1.05
		4	0.09	0.03	1.10	1.04	1.15
		5	0.08	0.04	1.09	1.00	1.18
		6	0.07	0.03	1.07	1.01	1.14
		7	0.11	0.03	1.12	1.07	1.18
		8	-0.04	0.03	0.96	0.91	1.01
		9	0.11	0.04	1.12	1.03	1.21

[a]Model was estimated using a generalized estimating equation with cohort as a panel variable and a exchangeable correlation structure
[b]The interaction between temporal pattern and cumulative morbidity could not be computed because there were no cohorts with these covariate patterns

Table A.6.6 Final multivariable logistic regression model[a] of the cumulative mortality risk within feedlot cattle cohorts (n = 7,447)

Covariate	P > χ2	Level	b	Robust S.E. (b)	OR	95% CI OR	
Intercept			-5.06	0.19			
Temporal pattern	0.1531	1	Referent				
		2	0.19	0.17	1.21	0.87	1.69
		3	-0.25	0.23	0.78	0.50	1.22
		4	-0.06	0.26	0.94	0.57	1.57
		5	0.15	0.20	1.16	0.78	1.73
		6	-0.18	0.20	0.83	0.57	1.23
		7	-0.28	0.23	0.76	0.48	1.18
Gender	0.0852	Male	Referent				
		Female	0.04	0.02	1.04	0.99	1.09
Arrival weight (kg)	0.0012	>409	Referent				
		363-408	0.02	0.17	1.02	0.73	1.41
		318-362	0.12	0.14	1.13	0.86	1.48
		272-317	-0.01	0.13	0.99	0.76	1.28
		227-271	0.04	0.14	1.04	0.79	1.37
		182-226	0.40	0.16	1.49	1.09	2.05
		<182	0.44	0.18	1.55	1.08	2.22
Cumulative morbidity	<0.0001	0-<5%	Referent				
		5-<10%	0.42	0.08	1.52	1.30	1.77
		10-<20%	0.99	0.08	2.70	2.31	3.17
		≥ 20%	1.77	0.09	5.88	4.90	7.04
Risk code	<0.0001	Low	Referent				
		High	0.24	0.04	1.27	1.19	1.36
Temporal pattern X	0.0005	1 X ≥ 409	Referent				
Arrival weight		1 X 363-408	Referent				
		1 X 318-362	Referent				
		1 X 272-317	Referent				
		1 X 227-271	Referent				
		1 X 182-226	Referent				
		1 X <182	Referent				
		2 X ≥ 409	Referent				
		2 X 363-408	-0.11	0.21	0.89	0.60	1.34
		2 X 318-362	-0.08	0.18	0.93	0.66	1.31
		2 X 272-317	0.10	0.17	1.11	0.79	1.56
		2 X 227-271	0.15	0.18	1.16	0.82	1.66
		2 X 182-226	0.02	0.20	1.02	0.69	1.52
		2 X <182	-0.02	0.23	0.98	0.62	1.55
		3 X ≥ 409	Referent				

		3 X 363-408	0.31	0.26	1.36	0.82	2.24
		3 X 318-362	0.26	0.24	1.30	0.82	2.07
		3 X 272-317	0.61	0.24	1.83	1.15	2.92
		3 X 227-271	0.63	0.25	1.87	1.16	3.03
		3 X 182-226	0.32	0.26	1.37	0.82	2.29
		3 X <182	0.74	0.30	2.09	1.16	3.75
		4 X ≥ 409	Referent				
		4 X 363-408	0.20	0.29	1.22	0.69	2.15
		4 X 318-362	0.25	0.27	1.28	0.76	2.17
		4 X 272-317	0.34	0.27	1.40	0.83	2.37
		4 X 227-271	0.49	0.27	1.63	0.95	2.78
		4 X 182-226	0.01	0.29	1.01	0.57	1.78
		4 X <182	0.38	0.34	1.46	0.75	2.86
		5 X ≥ 409	Referent				
		5 X 363-408	0.02	0.23	1.02	0.65	1.61
		5 X 318-362	0.01	0.21	1.01	0.67	1.53
		5 X 272-317	0.26	0.21	1.29	0.86	1.95
		5 X 227-271	0.33	0.22	1.39	0.91	2.13
		5 X 182-226	0.13	0.24	1.13	0.71	1.81
		5 X <182	-0.60	0.35	0.55	0.27	1.10
		6 X ≥ 409	Referent				
		6 X 363-408	0.29	0.23	1.33	0.85	2.09
		6 X 318-362	0.30	0.21	1.35	0.90	2.02
		6 X 272-317	0.43	0.21	1.54	1.02	2.32
		6 X 227-271	0.65	0.22	1.91	1.25	2.93
		6 X 182-226	0.46	0.24	1.58	0.99	2.54
		6 X <182	0.96	0.27	2.61	1.55	4.39
		7 X ≥ 409	Referent				
		7 X 363-408	0.12	0.27	1.13	0.67	1.90
		7 X 318-362	0.05	0.25	1.05	0.64	1.70
		7 X 272-317	0.52	0.25	1.69	1.04	2.74
		7 X 227-271	0.38	0.27	1.46	0.86	2.49
		7 X 182-226	0.29	0.29	1.33	0.75	2.35
		7 X <182	0.55	0.43	1.73	0.75	3.99
[b]Temporal pattern X	0.0001	1 X 0-<5%	Referent				
Cumulative morbidity		1 X 5-<10%	Referent				
		1 X 10-<20%	Referent				
		1 X ≥ 20%	Referent				
		2 X 0-<5%	Referent				
		2 X 5-<10%	0.11	0.10	1.11	0.92	1.34
		2 X 10-<20%	-0.14	0.10	0.87	0.72	1.05
		2 X ≥ 20%	-0.23	0.11	0.79	0.64	0.98

191

			Coef	SE	OR	LL	UL
3 X 0-<5%		Referent					
3 X 5-<10%		0.24	0.11	1.27	1.02	1.56
3 X 10-<20%		-0.02	0.11	0.98	0.79	1.22
3 X ≥ 20%		-0.24	0.12	0.79	0.62	0.99
4 X 0-<5%		Referent					
4 X 5-<10%		-0.02	0.11	0.98	0.79	1.23
4 X 10-<20%		-0.16	0.12	0.85	0.67	1.07
4 X ≥ 20%		-0.48	0.14	0.62	0.47	0.81
5 X 0-<5%		Referent					
5 X 5-<10%		0.10	0.09	1.10	0.92	1.33
5 X 10-<20%		-0.13	0.11	0.88	0.71	1.08
5 X ≥ 20%		-0.50	0.12	0.61	0.48	0.77
6 X 0-5%		Referent					
6 X 5-<10%		-0.08	0.11	0.92	0.74	1.15
6 X 10-<20%		-0.27	0.15	0.76	0.57	1.02
6 X ≥ 20%		-0.64	0.33	0.53	0.27	1.02
7 X 0-<5%		Referent					
7 X 5-<10%		-0.24	0.36	0.79	0.39	1.60
7 X 10-<20%		N/A[b]					
7 X ≥ 20%		N/A[b]					
Time	<0.0001	1	0.00				
		2	0.11	0.16	1.11	0.81	1.52
		3	-0.10	0.15	0.90	0.67	1.22
		4	-0.32	0.15	0.72	0.54	0.97
		5	-0.29	0.15	0.75	0.56	1.00
		6	-0.28	0.15	0.75	0.57	1.00
		7	-0.21	0.15	0.81	0.60	1.08
		8	-0.06	0.17	0.95	0.67	1.33
		9	0.08	0.15	1.08	0.80	1.45
		10	0.01	0.16	1.01	0.73	1.38
		11	0.12	0.15	1.13	0.83	1.52
		12	-0.07	0.16	0.93	0.68	1.28
		13	0.03	0.15	1.03	0.77	1.39
		14	-0.05	0.15	0.95	0.71	1.27
		15	-0.10	0.14	0.91	0.68	1.20
		16	-0.06	0.15	0.94	0.70	1.25
		17	-0.03	0.15	0.97	0.73	1.29
		18	0.17	0.15	1.19	0.89	1.59
		19	0.09	0.15	1.09	0.81	1.47
		20	0.24	0.15	1.27	0.95	1.70
		21	0.11	0.15	1.11	0.84	1.48
		22	-0.11	0.15	0.90	0.66	1.21

		23	-0.10	0.14	0.91	0.68	1.20
		24	-0.42	0.16	0.66	0.48	0.90
		25	-0.30	0.14	0.74	0.56	0.98
		26	-0.22	0.15	0.80	0.59	1.08
		27	-0.22	0.15	0.80	0.60	1.07
		28	-0.26	0.14	0.77	0.58	1.02
		29	-0.11	0.15	0.89	0.67	1.19
		30	-0.28	0.15	0.76	0.57	1.01
		31	-0.18	0.15	0.84	0.62	1.13
		32	-0.18	0.15	0.84	0.62	1.13
		33	-0.46	0.15	0.63	0.47	0.85
		34	-0.22	0.15	0.80	0.60	1.07
		35	-0.23	0.16	0.80	0.58	1.09
		36	-0.16	0.34	0.85	0.44	1.65
		37	0.44	0.21	1.56	1.03	2.35
Feedlot	<0.0001	1	0.00				
		2	0.16	0.04	1.18	1.09	1.27
		3	0.42	0.05	1.52	1.38	1.66
		4	0.37	0.04	1.45	1.34	1.56
		5	1.15	0.07	3.15	2.73	3.64
		6	0.35	0.04	1.43	1.31	1.55
		7	0.57	0.04	1.76	1.61	1.92
		8	0.49	0.04	1.63	1.50	1.76
		9	0.06	0.06	1.06	0.95	1.19

[a]Model was estimated using a generalized estimating equation with cohort as a panel variable and a exchangeable correlation structure
[b]The interaction between temporal pattern and cumulative morbidity could not be computed because there were no cohorts with these covariate patterns

Table A.6.7 Final multivariable logistic regression model[a] of cumulative retreatment risk within feedlot cattle cohorts (n = 7,447)

Covariate	P > χ2	Level	b	Robust S.E. (b)	OR	95% CI OR	
Intercept			-1.17	0.20			
Temporal pattern	0.62560	1	Referent				
		2	-0.10	0.19	0.91	0.62	1.31
		3	-0.30	0.29	0.74	0.42	1.30
		4	-0.50	0.29	0.61	0.34	1.07
		5	-0.33	0.27	0.72	0.42	1.24
		6	-0.30	0.38	0.74	0.35	1.57
		7	-0.36	0.59	0.70	0.22	2.23
Gender	0.07450	Male	Referent				
		Female	0.05	0.03	1.05	0.99	1.11
Arrival weight (kg)	0.26900	>409	Referent				
		363-408	0.01	0.15	1.01	0.75	1.35
		318-362	0.03	0.13	1.03	0.81	1.32
		272-317	0.03	0.12	1.03	0.81	1.31
		227-271	-0.12	0.13	0.88	0.68	1.15
		182-226	-0.13	0.15	0.88	0.66	1.18
		<182	-0.46	0.28	0.63	0.36	1.09
Cumulative morbidity	<0.0001	0-<5%	Referent				
		5-<10%	0.22	0.10	1.24	1.03	1.50
		10-<20%	0.43	0.09	1.53	1.28	1.83
		≥ 20%	0.66	0.09	1.94	1.62	2.34
Risk code	<0.0001	Low	Referent				
		High	0.23	0.04	1.26	1.17	1.35
Temporal pattern X	0.0031	1 X ≥ 409	Referent				
Arrival weight		1 X 363-408	Referent				
		1 X 318-362	Referent				
		1 X 272-317	Referent				
		1 X 227-271	Referent				
		1 X 182-226	Referent				
		1 X <182	Referent				
		2 X ≥ 409	Referent				
		2 X 363-408	0.11	0.21	1.12	0.75	1.69
		2 X 318-362	0.19	0.18	1.21	0.85	1.72
		2 X 272-317	0.21	0.18	1.23	0.87	1.75
		2 X 227-271	0.38	0.19	1.46	1.01	2.12
		2 X 182-226	0.49	0.20	1.64	1.11	2.42
		3 X ≥ 409	Referent				
		2 X <182	0.78	0.33	2.17	1.14	4.15

		3 X 363-408	0.58	0.30	1.79	0.98	3.25
		3 X 318-362	0.42	0.28	1.53	0.87	2.66
		3 X 272-317	0.61	0.29	1.85	1.06	3.23
		3 X 227-271	0.79	0.29	2.20	1.24	3.92
		3 X 182-226	0.86	0.30	2.36	1.30	4.26
		3 X <182	1.30	0.43	3.66	1.57	8.55
		4 X ≥ 409	Referent				
		4 X 363-408	0.54	0.31	1.72	0.94	3.16
		4 X 318-362	0.70	0.29	2.01	1.15	3.53
		4 X 272-317	0.77	0.29	2.15	1.22	3.79
		4 X 227-271	0.91	0.30	2.50	1.39	4.49
		4 X 182-226	0.72	0.31	2.05	1.11	3.78
		4 X <182	1.24	0.44	3.45	1.45	8.20
		5 X ≥ 409	Referent				
		5 X 363-408	0.47	0.29	1.59	0.91	2.80
		5 X 318-362	0.45	0.27	1.56	0.92	2.67
		5 X 272-317	0.45	0.28	1.56	0.91	2.68
		5 X 227-271	0.60	0.28	1.81	1.04	3.17
		5 X 182-226	0.77	0.30	2.16	1.20	3.89
		5 X <182	0.77	0.48	2.15	0.84	5.53
		6 X ≥ 409	Referent				
		6 X 363-408	0.67	0.40	1.96	0.90	4.25
		6 X 318-362	0.55	0.38	1.73	0.82	3.65
		6 X 272-317	0.39	0.39	1.48	0.69	3.16
		6 X 227-271	0.66	0.40	1.93	0.89	4.21
		6 X 182-226	0.63	0.43	1.88	0.82	4.35
		6 X <182	0.76	0.63	2.14	0.62	7.35
		7 X ≥ 409	Referent				
		7 X 363-408	1.01	0.62	2.75	0.81	9.29
		7 X 318-362	0.36	0.62	1.44	0.43	4.81
		7 X 272-317	0.40	0.64	1.49	0.43	5.22
		7 X 227-271	0.16	0.65	1.17	0.33	4.18
		7 X 182-226	0.11	0.70	1.12	0.28	4.39
		7 X <182	-0.21	0.82	0.81	0.16	4.09
[b]Temporal pattern X Cumulative morbidity	0.0006	1 X 0-<5%	Referent				
		1 X 5-<10%	Referent				
		1 X 10-<20%	Referent				
		1 X ≥20%	Referent				
		2 X 0-<5%	Referent				
		2 X 5-<10%	-0.05	0.12	0.95	0.74	1.21
		2 X 10-<20%	0.06	0.12	1.06	0.84	1.33
		2 X ≥ 20%	-0.09	0.12	0.91	0.72	1.16

195

3 X 0-<5%	Referent				
3 X 5-<10%	-0.03	0.13	0.97	0.75	1.25
3 X 10-<20%	0.03	0.13	1.03	0.80	1.33
3 X ≥ 20%	-0.28	0.13	0.75	0.59	0.97
4 X 0-<5%	Referent				
4 X 5-<10%	-0.11	0.14	0.90	0.68	1.19
4 X 10-<20%	-0.31	0.14	0.73	0.56	0.96
4 X ≥ 20%	-0.19	0.15	0.83	0.61	1.11
5 X 0-<5%	Referent				
5 X 5-<10%	-0.12	0.12	0.89	0.70	1.12
5 X 10-<20%	-0.06	0.12	0.94	0.74	1.19
5 X ≥ 20%	-0.30	0.13	0.74	0.57	0.96
6 X 0-<5%	Referent				
6 X 5-<10%	-0.41	0.14	0.66	0.50	0.88
6 X 10-<20%	-0.38	0.18	0.69	0.48	0.98
6 X ≥ 20%	-0.44	0.21	0.65	0.43	0.97
7 X 0-<5%	Referent				
7 X 5-<10%	-1.42	0.56	0.24	0.08	0.72
7 X 10-<20%	N/A[b]				
7 X ≥ 20%	N/A[b]				

Time	<0.0001	1	0.00			
		2	0.09	0.17	1.09	0.78	1.52
		3	-0.03	0.16	0.97	0.71	1.34
		4	-0.43	0.17	0.65	0.47	0.91
		5	-0.48	0.16	0.62	0.45	0.85
		6	-0.55	0.16	0.57	0.42	0.78
		7	-0.81	0.17	0.45	0.32	0.62
		8	-0.54	0.18	0.58	0.41	0.84
		9	-0.28	0.17	0.76	0.54	1.06
		10	-0.33	0.18	0.72	0.50	1.02
		11	-0.20	0.18	0.82	0.58	1.17
		12	-0.27	0.20	0.76	0.51	1.13
		13	-0.27	0.18	0.76	0.54	1.08
		14	-0.32	0.17	0.73	0.52	1.00
		15	-0.36	0.16	0.70	0.51	0.96
		16	-0.34	0.17	0.71	0.51	0.99
		17	-0.26	0.16	0.77	0.56	1.06
		18	-0.24	0.17	0.79	0.57	1.09
		19	-0.36	0.17	0.70	0.50	0.98
		20	-0.23	0.17	0.80	0.57	1.12
		21	-0.95	0.17	0.39	0.28	0.53
		22	-0.84	0.18	0.43	0.30	0.62

196

		23	-0.73	0.17	0.48	0.35	0.67
		24	-0.72	0.18	0.49	0.34	0.70
		25	-0.69	0.16	0.50	0.37	0.69
		26	-0.61	0.17	0.54	0.39	0.75
		27	-0.82	0.17	0.44	0.32	0.61
		28	-0.69	0.16	0.50	0.37	0.69
		29	-0.54	0.16	0.58	0.43	0.79
		30	-0.49	0.16	0.61	0.45	0.83
		31	-0.34	0.16	0.71	0.52	0.97
		32	-0.51	0.17	0.60	0.43	0.83
		33	-0.86	0.16	0.42	0.31	0.58
		34	-0.50	0.16	0.60	0.44	0.83
		35	-0.57	0.19	0.56	0.39	0.82
		36	-1.14	0.38	0.32	0.15	0.68
		37	0.88	0.29	2.42	1.38	4.24
Feedlot	<0.0001	1	0.00				
		2	-0.08	0.04	0.93	0.86	1.00
		3	0.31	0.05	1.37	1.24	1.51
		4	0.07	0.04	1.07	0.99	1.17
		5	-1.15	0.17	0.32	0.23	0.44
		6	-0.06	0.05	0.94	0.85	1.03
		7	-0.64	0.07	0.52	0.46	0.60
		8	0.49	0.05	1.63	1.48	1.79
		9	-0.36	0.07	0.70	0.61	0.79

[a]Model was estimated using a generalized estimating equation with cohort as a panel variable and a exchangeable correlation structure

[b]The interaction between temporal pattern and cumulative morbidity could not be computed because there were no cohorts with these covariate patterns