ESSAYS ON AGRICULTURAL MARKETING AND CLIMATE RISK

A Dissertation

by

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ABSTRACT

This dissertation is composed of three essays. The first two essays investigate the existence and sources of grading bias in yield and quality grade. The yield and quality grades represent the amount and quality of meat from beef cattle, respectively. The first essay employs a cutoff point analysis to identify the possible sources of grader bias related to quality grade. The results indicate that quality grades graded by USDA human graders were noticeably different from those measured by camera grading systems. The findings from comparative analyses suggest seasonality in Choice-Select spread, consumers' beef demand, and carcass characteristics could influence human graders' grading. The histogram and cutoff estimation analyses present the existence of a central tendency bias in quality grading. Graders had a tendency to call central grade instead of extreme grades.

The second essay applies a non-parametric approach to a cutoff point estimation model to investigate the existence and potential sources of grading bias in yield grade. The non-parametric model was adopted to enhance the consistency of the estimation model due to the non-normality of grading errors. First, the essay found that graders evaluated beef carcasses more strictly during the 2007-2008 financial crisis. During the crisis, corn prices increased, and beef consumption decreased. These changes in the economic situation were not in favor of producers and packers. Graders also could be aware of the effect of their miscalls on producers' and packers' profitability. Given this

economic condition and graders' awareness, graders could try to grade beef carcasses more strictly during the crisis. Second, the degree of grading bias was amplified when graders graded the lowest and highest grades. The low frequency of grading the extreme grades could lead to the difference in grading bias across grades. Third, more generous grading behavior was observed during weekend compared to workdays. We attempted to explain these findings using the weekend effect that indicates a different pattern in human graders' behavior before, during, or after weekends compared to their behavior during workdays.

The third essay investigates the impact of weather stress on beef production. This essay provides evidence on how heat and cold stress influenced beef carcass attributes such as yield index, marbling score, ribeye area, and fat thickness, which determine the market value of a beef carcass. The results indicated that longer exposure to cold and heat stress led to deteriorated yield index. Meanwhile, marbling score was only worsened by cold stress, but it was improved by heat stress. Given these results, this essay also conducted a simulation analysis to determine the effect of weather stress on the profitability of beef cattle producers. The results showed that weather stress steadily increased producers' losses, as improved marbling score attributed to heat stress had a limited impact on profitability. The essay also calculated fair premium rates of a weather-index livestock insurance product that can be used to mitigate potential losses from extreme weather.

DEDICATION

To my lovely wife and daughter, for their love and support

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Contributors

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All work for the dissertation was completed by the student, under the advisement of Dr. Ariun Ishdorj of the Department of Agricultural Economics.

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1. INTRODUCTION

Agricultural marketing plays an important role in developing related industries and establishing an agricultural policy. The system provides a fundamental infrastructure to enhance market competitiveness to benefit consumers and producers (USDA AMS 2015). The system also helps communicate the quality of agricultural products to consumers and assists producers in differentiating themselves from their competitors. One of the important marketing systems in the agricultural industry is the beef grading system. The USDA beef grading standards are comprised of USDA quality and yield grade designed to assess eating quality and amount of lean edible meat from a carcass, respectively. Livestock producers can predict the market value of livestock sold by producers and bought by packers and beef sold by packers are affected by these standardized grades. Producers have an incentive to produce high-quality beef cattle because the system is designed to provide a financial reward for higher beef quality. Consumers can make their informed purchasing decisions using beef grades and labels. In short, the system makes the marketing process simpler and communication between producers and consumers easier (Field, 2007).

The effectiveness of the beef grading system is guaranteed by accurate and precise grading. In reality, however, graders employed by USDA determine grades through a visual inspection within a few seconds. Although USDA graders are well trained and independent of both producers and packers, the nature of the grading process might lead to grading errors. These errors could diminish the farmer’s incentive to produce a higher-quality product (Chalfant and Rexton 2003) and reduce the efficiency of the marketing process.

In 2006, USDA approved two camera-based grading systems in order to improve beef carcass grading accuracy and uniformity within the industry. Nine packing plants use these instruments to assist in grading operations for approximately 40 percent of the beef carcasses graded each day by USDA (USDA 2013). In August 2014, the USDA Agricultural Marketing Service (AMS) sought public input on possible revisions to the U.S. Standards for Grades of Carcass Beef to help adjust for recent improvements and trends in animal raising and feeding. Although AMS has been working on improving the accuracy of beef grading, relatively few studies looked at the presence and sources of grader errors. Hueth, Marcoul, and Lawrence (2007) used a behavior model and found the existence of grader bias in assigning yield grade. Mafi, Harsh, and Scanga (2013) found that cameras/instruments are more accurate and consistent than USDA graders in assessing marbling score to determine quality grade. They also found that camera grading could reduce grader-to-grader and plant-to-plant variations.

Grading accuracy is crucial for the efficiency of the beef marketing system and the promotion of beef quality. The impact of grading errors on efficiency and promotion can be minimized, if the errors are not systematically biased across time and locations (Hueth, Marcoul, and Lawrence 2007). When the errors are systematically biased across time or locations, users of the system cannot trust the grading system. The unreliable system cannot play its role effectively. The first and second essay focus on investigating the presence of grading errors and whether or not grading errors are systematically biased across time.

The estimated death losses of beef cattle due to a severe weather condition increase 122.1% from 2005 ($172 million) to 2015 ($382 million) (USDA 2006; USDA 2017). This increasing trend of beef cattle death losses due to severe weather condition suggests that the importance of managing weather-related risk is elevating. Climate risk management is also an important factor in beef production because it is directly related to the profitability of beef cattle producers. It is, thus, significant to investigate the influence of weather stress on beef cattle production. As researchers recognize the importance of managing climate risk in cattle production, many studies have addressed the issues. However, there are a few topics, which have not sufficiently investigated due to the lack of necessary data and econometric tools.

In the last essay, thus, we investigate the impact of climate risk on beef production using a unique dataset and a suitable econometric approach. The essay examines the impact of heat and cold stress on beef carcass traits such as the yield index, marbling score, ribeye area, and fat thickness, respectively. These traits determine the market value of a beef carcass. Given the estimated relations between weather stress and beef production, the essay simulates producers' losses and calculates fair premium rates for weather index-based livestock insurance. Finally, the essay also examines how the variation in corn prices and transportation stress influenced beef cattle production.

2. EXPLORING THE EXISTENCE OF GRADER BIAS IN BEEF GRADING[*]

2.1 Introduction

The United States Department of Agriculture (USDA) beef carcass grading standards are comprised of USDA quality and yield grades, which are designed to assess the eating quality and the amount of lean edible meat from a carcass, respectively. Producers use these grades to roughly predict the market value of cattle they sell to packers and have a financial incentive to produce the best tasting and high-quality beef under the USDA grading system. Consumers make informed purchasing decisions using USDA quality grades and labels. In short, the system simplifies the marketing process and makes communication among producers, packers, and consumers easier (Field 2007).

The integrity of the beef grading system is assured by accurate and precise grading. In reality, however, graders employed by the USDA determine carcass grades by a brief visual inspection that takes only a few seconds. Although USDA graders are well-trained and independent of both producers and packers, the nature of the grading process could lead to grading errors. These errors could diminish the incentive to produce a higher-quality product (Chalfant and Rexton 2003). When quality grades called by USDA graders are lower than actual quality grades, cattle producers take a loss on transactions with packers. In the case of beef consumers, they have to pay more (or

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[*] "Exploring the Existence of Grader Bias in Beef Grading" by Ju Won Jang, Ariun Ishdorj, David P. Anderson, Tsengeg Puurevjav, and Garland Dahlke, The Journal of Agricultural and Applied Economics, 49, 3(2017): 467-489.

less) than the actual value of beef due to the grading errors. The grading errors in quality grades impede the communication among beef consumers, producers and packers. The influence of grading errors on the efficiency of the market and promotion of beef can be minimized, if the errors are not systematically biased across time and location (Hueth, Marcoul, and Lawrence 2007). Grading accuracy and consistency, thus, are crucial for improving producers', packers', and consumers' confidence in the efficiency of the beef marketing system.

In 2006, two camera-based grading systems were approved by the USDA in order to improve beef carcass grading accuracy and uniformity within the industry[1]. In August 2014, the USDA Agricultural Marketing Service (USDA-AMS) sought public input for possible revisions to the *U.S. Standards for Grades of Carcass Beef* to help adjust for recent improvements and trends in the raising and feeding of cattle. Although the USDA-AMS has been working on improving the accuracy of beef grading, there are relatively few studies that looked at the presence and sources of grader bias. Mafi, Harsh, and Scanga (2013) documented that cameras/instruments were more accurate and consistent than the USDA graders in assessing marbling score to determine quality grade. They also found that cameras/instruments reduced grader-to-grader and plant-to-plant variations. Hueth, Marcoul, and Lawrence (2007) used a behavior model and showed the existence of grader bias in assigning yield grade. They defined grading as biased when the distribution of the "true" (the grade that should be assigned according to

[1] Nine packing plants use these instruments to assist in grading operations for approximately 40 percent of the beef carcasses graded each day by USDA (USDA 2013).

the USDA standards) yield grade systemically differs from that of the ‘called’ (the grade actually assigned by a USDA grader) yield grade. To measure the divergence of two distributions, they estimated a mean and variance of the true yield index[2] and compared them with the sample mean and standard deviation of the index. They also estimated cutoff values for each yield grade to capture the USDA graders’ behavior.

The current study builds on the previous literature by looking for evidence of the existence and possible sources of grading errors using data from a large-scale Midwest packing plant from 2005 through 2008. The data on quality grade called by USDA graders (‘called’ quality grade) and ‘camera-graded’ quality grade of each carcass were provided along with year, month, and day of the week when cattle were processed.

The specific objectives of this study are threefold. First, we analyzed the difference between ‘called’ and ‘camera-graded’ quality grade. Then, using these given quality grades, we estimated the cutoff points for each quality grade (e.g. Choice or Select) and compared them with the USDA standards cutoff points for each grade. From the analysis, we expected to find possible sources of grading errors. One of the significant errors in ratings is known as "central tendency bias". The existence of central tendency bias may be shown in beef grading if USDA graders do not follow the USDA standards and have a tendency to call grades close to the mean and avoid calling extreme grades. Second, we further investigated the patterns of grading errors by conducting

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[2] To define its yield grade standard, the USDA uses the following equation: yield index = 2.50 + 2.5×fat thickness + 0.20×kph + 0.0038×weight – 0.32×ribeye area where kph refers to kidney, pelvic, and heart fat.

seasonal and annual analyses to extend the existing literature by estimating seasonal and annual cutoff points. Existing research documented seasonal changes in beef carcass characteristics (Gray *et al.* 2012), the number of cattle marketed, and consumer demand (McCully 2015). The patterns of estimated intervals for quality grades across seasons and years were compared with Choice-Select spread, physical characteristics of beef carcasses, and the number of slaughter cattle processed in order to help identify possible sources of grading errors. Finally, since the USDA intends to more widely utilize the camera grading system in the future, it is worthwhile to analyze and discuss the impact of potential changes on producers and packers. For this analysis, weekly weighted averages of premiums and discounts for each quality grade were collected from USDA-AMS 5-Area Weekly Direct Slaughter Reports. The premium and discount data, along with 'called' and 'camera-graded' quality grades, allow the measurement of the financial impact of fully utilizing the camera grading system on cattle producers and packers.

To our knowledge, this is the first study that quantifies the variations in beef quality grading by USDA graders and camera systems across seasons and years. In addition, we address the impact of increased utilization of cameras in grading on cattle producers and packers. These analyses were possible, because the data used contain a much larger number of observations over the years than those in earlier studies (Hueth, Marcoul, and Lawrence 2007; Mafi, Harsh, and Scanga 2013).

A few points must be made about the terminology and assumptions used in this research. The term "grader bias" in this paper does not imply deception or dishonesty, but simply that the called quality grade is different from the USDA standards. In this paper, we assume that 'camera-graded' quality grade is not identical with the "true" USDA quality grade. Grades determined by cameras can be biased due to the initial settings, sensitivity, accuracy, and errors related to calibration of cameras (Moore *et al.* 2010; Mafi, Harsh, and Scanga 2013). Furthermore, part of our data was collected before the camera grading system was officially approved by the USDA in 2006. Given that there are some errors that can be associated with camera grading, the quality grade measured by the camera is unlikely to be identical with the "true" quality grade. These factors led us to develop a different behavior model from the model developed in Hueth, Marcoul, and Lawrence (2007).

2.2 Model

There are eight USDA quality grades: Prime, Choice, Select, Standard, Commercial, Utility, Cutter, and Canner. The factors that are used to determine the quality grade are the degree of marbling and the maturity class, which are classified into 9 and 5 different levels[3], respectively. The degree of marbling and the maturity class are combined to determine the final quality grade (Hale, Goodson, and Savell, 2015). When slaughter cattle are processed before 42 months of age, their carcasses are categorized as Prime, Choice, Select, or Standard according to marbling score. If slaughter cattle are processed after 42 months of age, the carcasses are graded as Commercial, Utility, Cutter, or

[3] Degree of Marbling is segmented into abundant, moderately abundant, slightly abundant, moderate, modest, small, slight, traces, and practically devoid. Maturity classes are classified into A (9-30 month), B (30-42 month), C (42-72 month), D (72-96 month), and E (>96 month).

Canner. The USDA graders subjectively determine both maturity and marbling class based on the descriptions and illustrations provided in the standards and their own practical work experiences.

Results of the 2005 National Beef Quality Audit determined that more than 97% of carcasses in U.S. fed beef plants were classified as A-maturity (9-30 months) (Garcia *et al.* 2008). Hence, in this study we assume that maturity class was A (9-30 months) or B (30-42 months). Given the maturity class, the primary determinant of quality grade will be the marbling score. The analysis of this study includes beef carcasses which are graded as Prime, Choice, Select, and Standard. Given this exclusion, a model that uses marbling score as the determinant of the quality grade is specified as follows.

Let MSI_k be the Marbling Score Interval for quality grade k. These intervals allow us to express quality grade in a functional form:

(1) Quality Grade =

{k | Marbling Score ∈ MSI_k, k = Prime, Choice, Select, Standard ∣ Maturity ≤ 42 months}.

Let c_i be a 'called' quality grade, m_i be a 'camera-graded' quality grade, and t_i be a "true" quality grade for a carcass *i*. "True" quality grade is unobserved. Using these definitions, the 'called' and "true" quality grade can be expressed as follows:

(2) $c_i = m_i + u_i,\ u_i \sim N(0, \sigma_u^2), t_i = m_i + v_i,\ v_i \sim N(0, \sigma_v^2),$

where u_i, and v_i are error terms for 'called' and "true" quality grades, respectively. We assume that error terms are distributed normally with mean zero and standard deviations, σ_u and σ_v. This assumption allows the use of a likelihood function to estimate cutoff points and standard errors.

The USDA Standard Marbling Score Intervals ($\widehat{\mathrm{MSI}}_{\mathrm{k}}$) for each quality grade are $\widehat{\mathrm{MSI}}_{\mathrm{Prime}} = [8.0, +\infty)$, $\widehat{\mathrm{MSI}}_{\mathrm{Choice}} = [5.0, 8.0)$, $\widehat{\mathrm{MSI}}_{\mathrm{Select}} = [4.0, 5.0)$, and $\widehat{\mathrm{MSI}}_{\mathrm{Standard}} = (-\infty, 4.0)$. The $\widehat{\mathrm{MSI}}_{\mathrm{Prime}}$ means that USDA graders should call Prime when an observed marbling score is greater than or equal to 8.0. Other quality grades should be called in a similar way, in that a grade is 'called' when marbling score falls within the indicated interval.

Since our data indicates that the 'called' quality grade is not identical with the 'camera-graded' quality grade, we presume that the USDA graders have their own marbling score intervals, which could be different from those of the USDA standards. Using this premise, the USDA graders Marbling Score Intervals $\left(\widetilde{\mathrm{MSI}}_{\mathrm{k}}\right)$ are defined by the following implicit cutoff points ($\mathrm{C_k}$, $\mathrm{k} = \mathrm{Prime},\ \mathrm{Choice},\ \mathrm{Select},\ \mathrm{and\ Standard}$)

$\widetilde{\mathrm{MSI}}_{\mathrm{prime}} = \left[\mathrm{C}_{\mathrm{prime}},\ +\infty\right)$, $\widetilde{\mathrm{MSI}}_{\mathrm{choice}} = \left[\mathrm{C}_{\mathrm{choice}},\ \mathrm{C}_{\mathrm{prime}}\right)$,

$\widetilde{\mathrm{MSI}}_{\mathrm{select}} = [\mathrm{C}_{\mathrm{select}},\ \mathrm{C}_{\mathrm{choice}})$, and $\widetilde{\mathrm{MSI}}_{\mathrm{standard}} = (-\infty, \mathrm{C}_{\mathrm{select}})$.

If these implicit cutoff points are different from those of the USDA standards across time, then we can conclude that grader bias exists.

We assume that the 'called' quality grade and the probability of the 'called' quality grade being the "true" quality grade are independent. Then the likelihood function can be defined as follows:

$$(3) \qquad L^i(c_i, m_i \mid \sigma_u, \sigma_v, C_{prime}, C_{choice}, C_{select})$$

$$= \mathbf{I}(c_i = \text{standard})\left\{\Phi\left(\frac{C_{select} - m_i}{\sigma_u}\right) \times \Phi\left(\frac{4 - m_i}{\sigma_v}\right)\right\}$$

$$\times \mathbf{I}(c_i = \text{select})\left\{\left[\Phi\left(\frac{C_{choice} - m_i}{\sigma_u}\right) - \Phi\left(\frac{C_{select} - m_i}{\sigma_u}\right)\right] \times \left[\Phi\left(\frac{5 - m_i}{\sigma_v}\right) - \Phi\left(\frac{4 - m_i}{\sigma_v}\right)\right]\right\}$$

$$\times \mathbf{I}(c_i = \text{choice})\left\{\left[\Phi\left(\frac{C_{prime} - m_i}{\sigma_u}\right) - \Phi\left(\frac{C_{choice} - m_i}{\sigma_u}\right)\right]\right.$$

$$\left.\times \left[\Phi\left(\frac{8 - m_i}{\sigma_v}\right) - \Phi\left(\frac{5 - m_i}{\sigma_v}\right)\right]\right\}$$

$$\times \mathbf{I}(c_i = \text{prime})\left\{\left[1 - \Phi\left(\frac{C_{prime} - m_i}{\sigma_u}\right)\right] \times \left[1 - \Phi\left(\frac{8 - m_i}{\sigma_v}\right)\right]\right\}$$

where, **I**( ) is an indicator function, and $\Phi(\,)$ is the cumulative density function of the standard normal distribution. The likelihood function is derived from the assumption that the USDA graders call quality grade to maximize the probability of calling the "true" quality grade by using their own implicit intervals. Since the "true" quality grade is unknown to USDA graders, they call quality grade using visual inspection and their own implicit cutoff points. A log transformation of the likelihood function was used in the maximum likelihood estimation process. The estimated cutoff points provide information about grading behavior of USDA graders in assigning quality grades.

2.3 Data

The data used in the analysis provides information on 'called' and 'camera-graded' quality grades of beef carcasses from May 2005 to October 2008. Figure 2.1 presents the distribution of 'called' quality grade for the entire sample (Num. of Obs.=134,451[4]) and shows that 94.4% of beef carcasses were graded Choice or Select. While the 'called' quality grade was available for the entire sample, the 'camera-graded' quality grade was only available for the subsample of the data (Num. of Obs.=18,080). Because the values for both 'called' and 'camera-graded' quality grades are required to estimate the implicit cutoff points, the subsample (Num. of Obs.=18,080) of the entire data (Num. of Obs.=134,451) was used in estimating the cutoff points and conducting premium-discount analysis.

In our data, 'called' marbling grades were reported as USDA quality grades (Prime, Choice, Select, or Standard) and 'camera-graded' marbling scores were reported as numeric values (e.g. 5.0 for Small) for some of the carcasses in our sample and as a degree of marbling (e.g. Small 20) for the remaining carcasses. To make the marbling measurements consistent across carcasses and to estimate the cutoff points, we converted each degree of marbling into a numeric marbling score. Figure 2.2 shows the distribution of the numeric ('camera-graded') marbling scores. Each number on the horizontal axis of Figure 2.2 corresponds to a degree of marbling score.

As shown in Figures 2.1 and 2.3, the distributions of 'called' quality grade from the entire sample (Num. of Obs.=134,451) and the subsample (Num. of Obs.=18,080) used in the analysis were similar. Both distributions show that most carcasses were graded as Choice or Select. The distribution from the entire sample (subsample) shows

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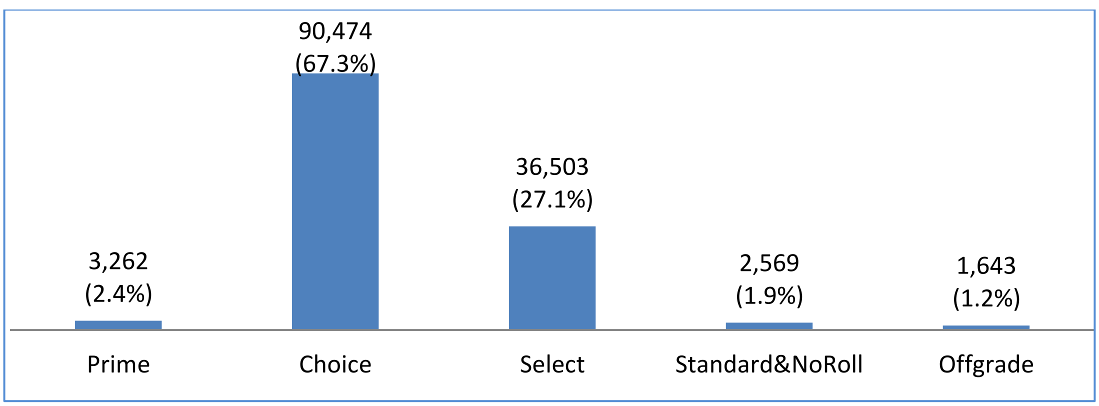
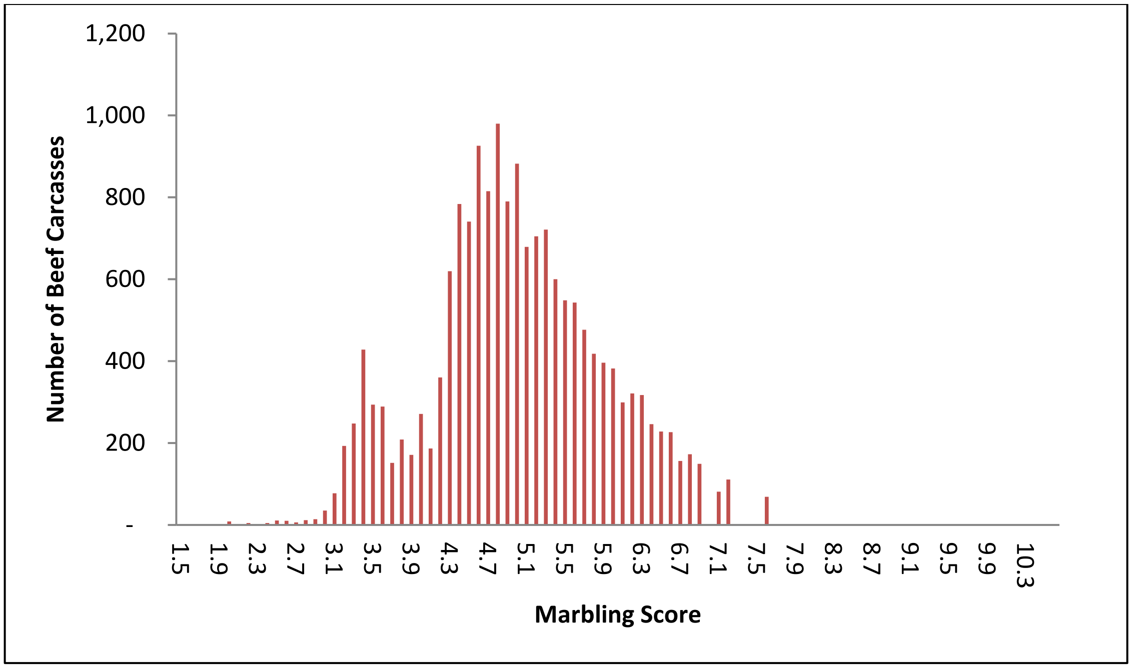
[4] The total number of observations in our data does not necessarily reflect all the cattle processed at the packing plants.

that the USDA graders graded 67.3% (70.2%) and 27.1% (27.2%) of carcasses as Choice and Select, respectively. The National Summary of Meat Graded Reports (USDA 2015b) announced by the USDA-AMS at the beginning of each year showed that most carcasses were graded either Choice or Select (Table 2.1). Although the distributions for 'called' and 'camera-graded' quality grades differ a bit, in percentage terms, from the national averages reported in Table 2.1, the shape of both 'called' and 'camera-graded' quality grades are similar to the national summary indicating that the sample data used in the analysis closely represents the national level data.



Source: The quality grade data were collected from a large-scale Midwest packing plant from May 2005 to October 2008.
Note: NoRoll represent carcasses not graded and have no USDA rolling stamp.

Figure 2.1. The Distribution of Quality Grade (Num. of Obs.=134,451, the number of head, percent of total graded in parentheses)



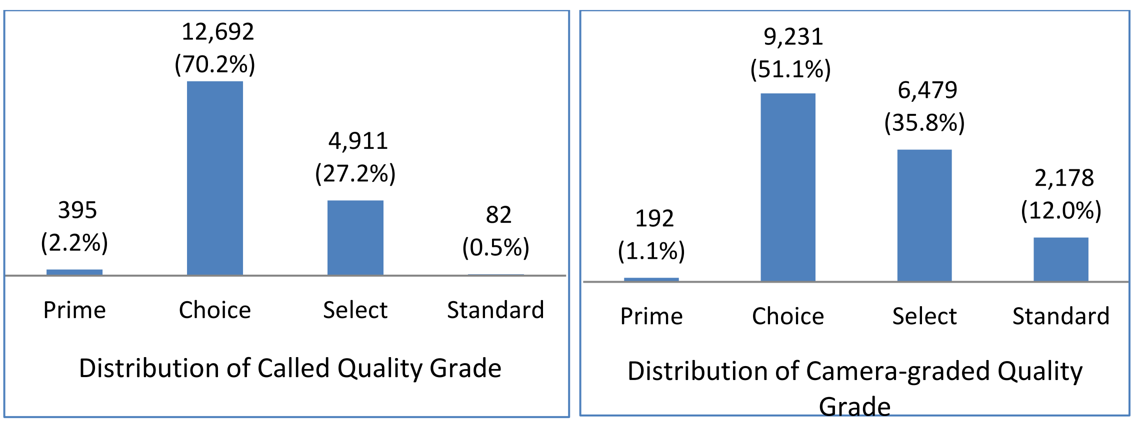
Source: The marbling score data were collected from a large-scale Midwest packing plant from May 2005 to October 2008.

Figure 2.2. The Distribution of the Numeric ('Camera-graded') Marbling Score (Num. of Obs.=18,080)

As shown in Figure 2.3, 70.2% (27.2%) of carcasses were graded as Choice (Select) by the USDA graders, whereas 51.1% (35.8%) of the carcasses were graded as Choice (Select) by cameras. This indicates that the USDA graders tend to call more Choice and less Select compared to cameras. Also, the two distributions show that the USDA graders were more generous in grading carcasses compared to cameras.

The distributions of 'camera-graded' quality grade given 'called' quality grade are shown in Figure 2.4. These conditional distributions allow us to analyze the differences between 'called' and 'camera-graded' quality grades. If there were no divergences between these two grades, then all the carcasses called as Prime by the

USDA graders should be graded as Prime by the cameras. However, as shown in Figure 2.4, out of 395 beef carcasses that were graded as Prime by the USDA graders, only 144 carcasses (36.5%) were graded as Prime by the cameras and the remaining 251 carcasses (63.5%) were graded as Choice. Furthermore, from all the carcasses graded as Choice by the USDA graders, 33.4% were graded as Select by the cameras. In the case of Select, 42.6% were graded as Standard by the cameras. These conditional distributions suggest that noticeable differences exist between 'called' and 'camera-graded' quality grades, except for Standard, and that the cameras generally assigned lower quality grades than the USDA graders.



Source: The quality grade data were collected from a large-scale Midwest packing plant from May 2005 to October 2008.

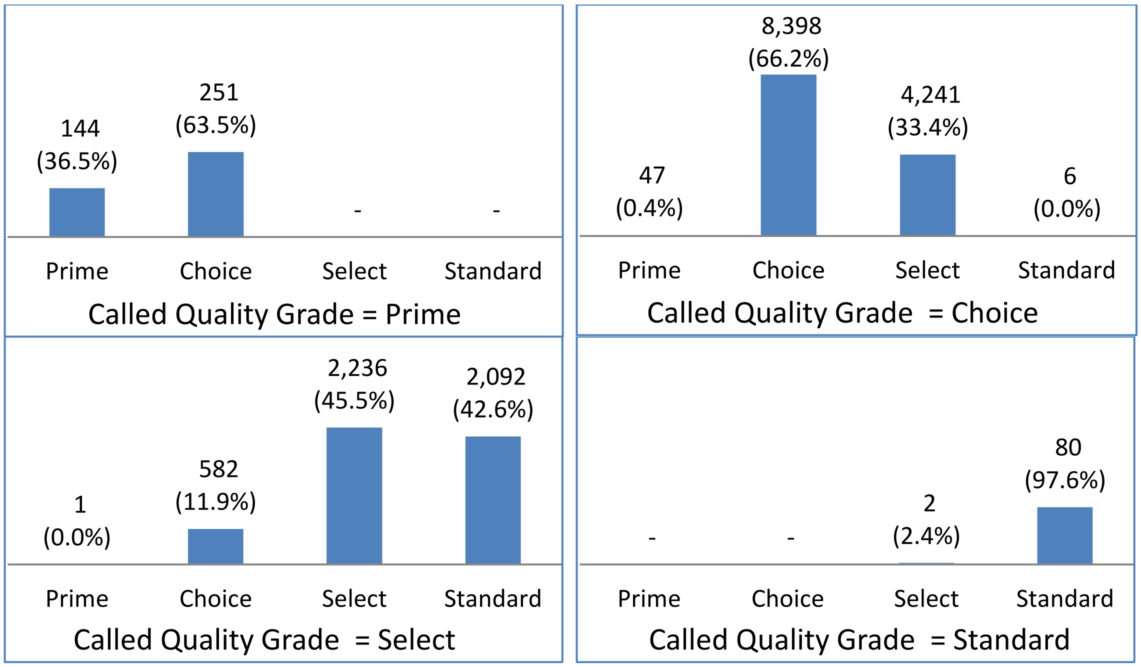
Figure 2.3. The Distribution of 'Called' and 'Camera-graded' Quality Grade (Num. of Obs. =18,080, the number of head, percent of total graded in parentheses)

Figure 2.5 illustrates the distribution of 'called' quality grade given 'camera-graded' quality grade. Almost all beef carcasses graded as Choice by the cameras were graded as Choice by the USDA graders. Similar patterns were observed for Prime, where a majority of carcasses graded as Prime by the cameras were also graded as Prime by the USDA graders. However, in the case of all carcasses graded as Select by the cameras, 65.6% were graded as Choice by the USDA graders and 96.1% of all carcasses graded as Standard by the cameras were graded as Select by the USDA graders. The comparison of conditional distributions in Figure 2.5 indicates that the difference between 'called' and 'camera-graded' quality grades was smaller when the USDA graders assessed Choice grade carcasses, but this was not the case for the other quality grade carcasses. This smaller divergence for Choice quality grade could be explained by Piazza and Izard (2009)'s findings: the more humans are exposed to the number of objects or sequence, the more likely they accurately repeat the sequence. As shown in Figure 2.3, 70.2% of carcasses in our observations were graded as Choice by the USDA graders. This could indicate that the USDA graders were more accurate in assessing Choice grade carcasses due to repeated exposures to Choice grade carcasses.

Table 2.1. National Summary of Meat Graded (Million Pounds, percent of total graded in parentheses)

	2005	2006	2007	2008	Total
Prime	602 (3.1)	577 (2.9)	525 (2.6)	595 (2.9)	2,298 (2.9)
Choice	11,133 (57.3)	11,367 (56.2)	11,655 (58.0)	12,459 (61.0)	46,614 (58.1)
Select	7,679 (39.5)	8,279 (40.9)	7,872 (39.1)	7,312 (35.8)	31,142 (38.8)
Standard	29 (0.1)	6 (0.0)	56 (0.3)	69 (0.3)	161 (0.2)
Total	19,441 (100)	20,229 (100)	20,109 (100)	20,435 (100)	80,214 (100)

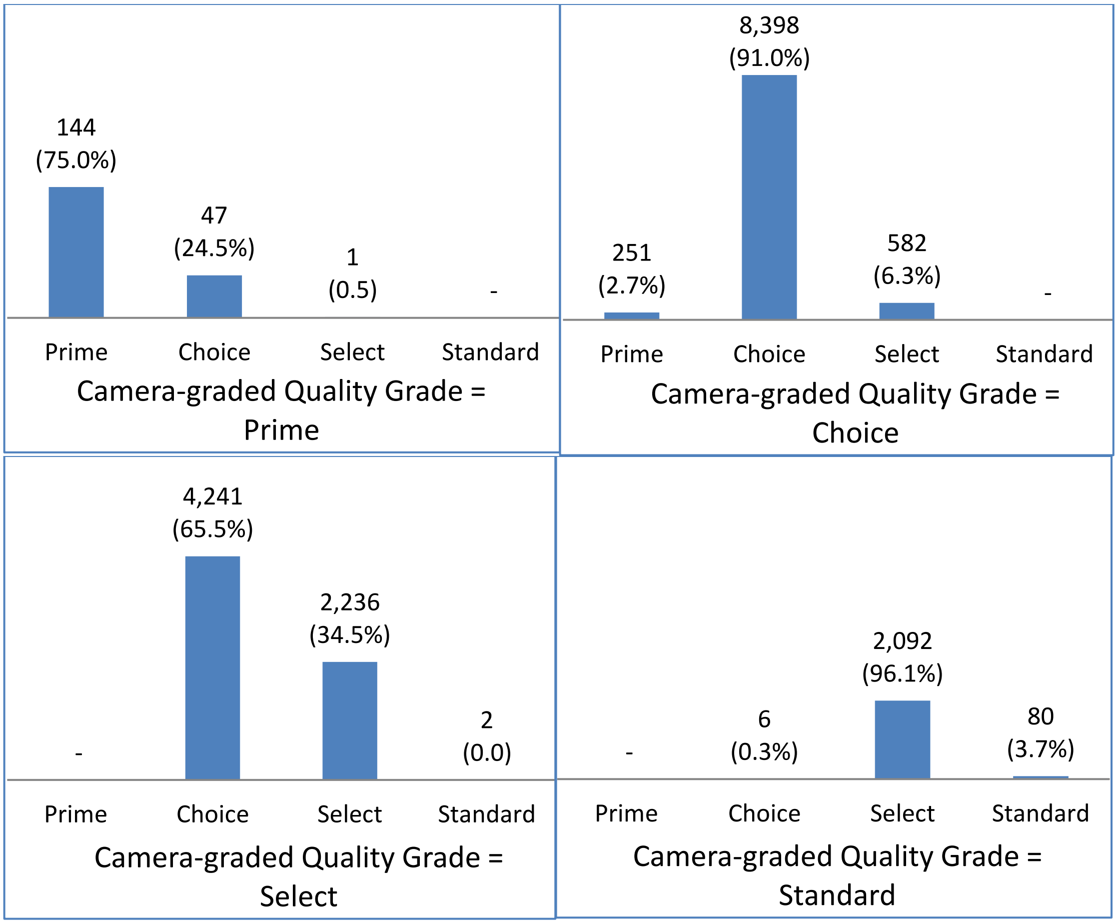
Source: AMS/USDA (http://www.ams.usda.gov/reports/meat-grading)



Source: The quality grade data were collected from a large-scale Midwest packing plant from May 2005 to October 2008.

Figure 2.4. The Distribution of 'Camera-graded' Quality Grade given 'Called' Quality Grade (Num. of Obs.=18,080, the number of head, percent of total graded in parentheses)

The distributional analyses in this section were not enough to confirm the existence of grader bias caused by the USDA graders since 'camera-graded' quality grade can also be different from the "true" USDA standard quality grade due to calibration errors or initial camera settings. The implicit cutoff points for each quality grade, thus, were estimated to further analyze the existence of grader bias and explore possible sources of the bias.



Source: The quality grade data were collected from a large-scale Midwest packing plant from May 2005 to October 2008.

Figure 2.5. The Distribution of 'Called' Quality Grade given 'Camera-graded' Quality Grade (Num. of Obs.=18,080, the number of head, percent of total graded in parentheses)

2.4 Results

2.4.1 Subsample Analysis

Cutoff points for each quality grade were estimated using equation (3) to identify the implicit USDA graders' interval. The existence of grading errors can be checked by comparing the estimated and USDA Standard cutoff points. As shown in Table 2.2, the estimated cutoff point for Prime was 8.90, which was greater than the USDA standards cutoff point of 8.00. The estimated interval for Prime, [8.90, +∞), indicates that the USDA graders called Choice when the marbling score was greater than 8.00 and that the USDA graders have higher standards for Prime.

Table 2.2 also shows that the estimated cutoff point for Choice was 4.50, which was lower than the cutoff point of 5.00 for Choice defined by the USDA standards. This difference between two cutoff points indicates that the USDA graders called Choice instead of Select when marbling score was less than 5.00[5]. The estimated cutoff points also identify the estimated implicit interval for Choice as [4.50, 8.90). This interval is much wider than the one from the USDA standards for Choice, [5.00, 8.00), indicating that the USDA graders had a tendency to call more Choice.

The estimated cutoff point for Select was 3.18. This value is smaller than 4.00, the value from the USDA standards for Select. Using the estimated cutoff points, the estimated intervals for Select and Standard quality grades were identified as [3.18, 4.50) and (-∞, 3.18), respectively. These intervals indicate that USDA graders called Select when marbling score was less than the USDA standards cutoff point of 4.00 for Select, again indicating that the USDA graders were generous in grading beef carcasses with less marbling.

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[5] If USDA graders follow the USDA standards, they should call Select when marbling score is greater than or equal to 4 and less than 5.

Table 2.2 Estimates of Standard Errors (σ_u, σ_v) and Cutoff Values (C_k)

Period	σ_u	σ_v	C_{Select}	C_{Choice}	C_{Prime}	ln L
USDA Standards			4.00	5.00	8.00	
Whole Sample Analysis	0.89 (0.04)	0.99 (0.01)	3.18 (0.01)	4.50 (0.01)	8.90 (0.15)	- 23,881.3
Seasonal Analysis						
Spring	0.89 (0.08)	0.96 (0.01)	3.13 (0.02)	4.55 (0.02)	8.59 (0.27)	- 10,340.4
Summer	0.72 (0.02)	0.86 (0.01)	2.24 (0.04)	4.32 (0.02)	7.97 (0.06)	-9,669.4
Fall	1.12 (0.06)	0.82 (0.02)	1.35 (0.24)	4.56 (0.05)	8.54 (0.15)	-1,938.0
Winter	0.66 (0.09)	0.63 (0.06)	3.64 (0.06)	4.81 (0.04)	8.79 (0.21)	-536.3
Annual Analysis						
2005	0.85 (0.05)	1.12 (0.01)	1.94 (0.09)	3.87 (0.02)	9.02 (0.11)	-3,419.7
2006	0.93 (0.12)	1.05 (0.01)	2.28 (0.14)	3.99 (0.05)	9.21 (0.41)	-8,911.7
2007	0.65 (0.05)	0.58 (0.02)	3.54 (0.04)	4.88 (0.01)	8.54 (0.18)	-5,774.1
2008	0.67 (0.04)	0.60 (0.03)	3.80 (0.04)	4.97 (0.02)	8.53 (0.09)	-2.656.6
Before (May 2005 – Jul 2007)	0.82 (0.04)	0.94 (0.01)	1.87 (0.09)	4.20 (0.02)	8.28 (0.12)	- 18,002.3
During (Aug 2007 –Oct 2008)	0.66 (0.04)	0.61 (0.03)	3.93 (0.02)	5.04 (0.02)	8.47 (0.08)	-3,396.3

Note: Standard errors in parentheses; All the estimated parameters were significant at 1% level; The estimated variables (σ_u, σ_v, C_{Select}, C_{Choice}, C_{Prime}, and ln L) in this table are defined in the equation (3).

Potential sources of grader bias could be identified by comparing the estimated and USDA standards intervals across quality grades. While the estimated intervals for Prime and Standard were narrower than the USDA standards intervals, the estimated intervals for Choice and Select were wider than the USDA standards intervals. This nonconformity can be explained by a central tendency bias. This bias was mostly researched by educationalists. Saal, Downey, and Lahey (1980) define this bias as a rater's (grader's) property or tendency to restrict a range of scores around a mean and to avoid awarding extreme scores. Existing studies in the area (Engelhard 1994; Myford and Wolfe 2009; Leckie and Goldstein 2011) found that there is a central tendency to a rater's scoring. Beef grading behavior is very similar to scoring behavior in schools. Both USDA graders and raters, although well trained, are human beings and evaluate subjects based on their subjective observations with given grading standards. These similarities have led us to consider the central tendency bias as the potential source of grader bias in beef carcass grading.

The narrow intervals for Prime and Standard quality grades mean that the USDA graders tend to avoid calling extreme grades. The wider intervals for Choice and Select indicate that graders preferred to call the quality grade around the mean marbling score of 5.10 for our sample (Table 2.3). These results indicate that USDA graders tend to call central grades and avoid calling extreme grades, i.e., Prime and Standard. These grading patterns are evidence of the central tendency bias in beef carcass grading.

Table 2.3. Summary Statistics of Marbling Score

Period	Num. of obs.	Mean	Std. Dev.
Whole Sample Period	18,080	5.10	1.04
Seasonal Analysis			
Spring (Mar - May)	7,785	5.01	1.00
Summer (Jun - Aug)	8,160	5.11	1.05
Fall (Sep - Nov)	1,485	5.34	1.03
Winter (Dec - Feb)	650	5.67	1.08
Annual Analysis			
2005 (May-Dec)	2,408	4.53	1.00
2006 (Jan-Dec)	6,304	4.79	1.01
2007 (Jan-Dec)	6,140	5.30	0.87
2008 (Jan-Oct)	3,228	5.77	0.95

Source: The marbling score data were collected from a large-scale Midwest packing plant from May 2005 to October 2008.
Note: Marbling score represents the eating quality of beef meat; The USDA Standard Marbling Score Intervals ($\widehat{\mathrm{MSI}}_{\mathrm{k}}$) for each quality grade are $\widehat{\mathrm{MSI}}_{\mathrm{Prime}} = [8.0, +\infty)$, $\widehat{\mathrm{MSI}}_{\mathrm{Choice}} = [5.0, 8.0)$, $\widehat{\mathrm{MSI}}_{\mathrm{Select}} = [4.0, 5.0)$, and $\widehat{\mathrm{MSI}}_{\mathrm{Standard}} = (-\infty, 4.0)$.

A reason for the central tendency bias in beef carcass grading may be found in the economic impact of quality grade to producers and packers. Producers can receive a premium or discount based on the quality grade of a beef carcass, if slaughter cattle were sold or priced based on their eventual grade. As shown in Table 2.4, Choice grade carcasses do not receive any premium or discount when priced based on a grid pricing system[6]. Under grid pricing, calling Choice is a way to make a smaller impact on the financial rewards/losses of producers and packers. Moreover, calling central grades, especially Choice, may be a way to avoid complaints from producers and packers. If USDA graders call extreme grades (Prime and Standard) more frequently, the probability of receiving complaints and re-grading requests could be higher. Because USDA graders are independent from producers and packers, they may have no intention of affecting the profit margin of both producers and packers through their grading. According to Hueth, Marcoul, and Lawrence (2007), packing plants hire a “tagger’ who identifies grader miscalls and requests re-grading. With the presence of a tagger, the USDA graders could become more generous in grading and have a tendency to call the central grades (Choice and Select) more often to avoid re-grading requests.

Table 2.4. USDA Reported Average Premiums and Discounts, (May 2005 – October 2008, $/cwt)

	Select	Prime	Choice	Standard
Premiums and Discounts	-9.78	15.43	0.00	-15.79

Source: USDA AMS National Weekly Direct Slaughter Cattle – Premiums and Discounts Report.

[6] There are three cattle pricing methods: live weight pricing, dressed weight pricing, and grid pricing. While the price of carcass is determined by ‘called’ yield and quality grade under grid pricing, the price is determined based on the expected value under live and dressed weight pricing.

2.4.2 Seasonal and Annual Analyses

Dynamics in beef carcass grading were analyzed by estimating seasonal and annual cutoff points and comparing them with the USDA standards. The results reported in Table 2.2 show that the estimated cutoff points for Prime varied significantly by season. The estimated cutoff point for Prime in the summer was 7.97, which was close to the USDA standards cutoff point for Prime. With respect to other seasons, the estimated cutoff points for Prime were noticeably higher than the USDA standards, indicating that during those seasons the USDA graders were much stricter in grading high quality beef carcasses compared to summer. The estimated interval for Choice in the summer, [4.32, 7.97), was narrower than those for other seasons, however the cutoff point of 4.32 was smaller compared to the USDA standards of 5.00, indicating that USDA graders were more generous and graded Select carcasses as Choice. The estimated interval for Select was the widest in fall and narrowest in winter. These seasonal differences in the estimated intervals and cutoff points can be caused by many factors such as seasonality in the Choice-Select spread, the volume of carcasses processed, the physical characteristics of beef carcass, and many other factors.

The Choice-Select spread, which is defined as the difference between the Choice and Select wholesale boxed-beef values, is used as an indicator of demand for high quality beef in the industry (McCully 2015). For example, when the Choice-Select spread reaches a high level (>$8/cwt), the industry assumes strong demand for high marbled beef, such as Choice, and when the spread is low (<$3/cwt), the industry assumes weak demand for Choice (McCully 2015).

In this paper, the Choice-Select spread data were collected from USDA-AMS 5-Area Weekly Direct Slaughter Reports for the period covered in our data and were summarized in Figure A.1. As illustrated in Figure A.1, the average Choice-Select spread peaked during the cookout month, May, and during the holiday months, November through January, indicating a high demand for Choice beef during these months. The spread decreased significantly after May and the holidays indicating the lower demand for Choice beef. Especially, the spread in summer (June - August) was relatively lower than those for other seasons. It is also true that beef supplies do tend to increase in summer. When comparing the patterns of the Choice-Select spread with those of the estimated intervals, we can argue that the low Choice-Select spread (low demand for Choice beef) influenced the narrow interval for Choice (calling less Choice) in summer compared to other seasons. The similarity in two patterns suggests that the demand for specific quality grade beef possibly influences the grading behavior.

As reported in Table 2.3, the majority of cattle in our sample were processed in spring and summer seasons, 43.1% and 45.1%, respectively, and in 2006 and 2007, indicating that for our sample the volume of slaughter cattle fluctuated greatly by season and year. The seasonality in number of slaughter cattle processed can be explained by the fact that the majority of calves are born in the spring months, weened in fall, and either backgrounded or placed on feed during October and November. The majority of these cattle are marketed and slaughtered during the summer months or later of the following year. These trends in seasons and years from our findings are consistent with the national averages reported in the monthly *Cattle on Feed* report provided by USDA

NASS (NASS, USDA 2015) and summarized in Figure A.2. for the time period covered in our data. Marketing of cattle tends to be highest in May through August of every year, which covers the last month of spring and all the months of summer. During the spring and summer months, the busy time of the year, USDA graders were more generous and were more likely to call Choice when the actual quality grade was Select. The estimated cutoff points for Choice in fall and winter were 4.56 and 4.81, respectively, and were closer to 5.00, the USDA standards cutoff for Choice, compared to spring and summer. Seasonal variations in the number of slaughter cattle processed at the packing plants can influence the grades called by USDA graders. Graders had a tendency to call more central grades during the busy seasons of the year which may be associated with taking shorter breaks, working longer hours, and/or using more temporary help.

We observed seasonal and yearly variations in carcass characteristics such as marbling score (Table 2.3), ribeye area, fat thickness, and hot carcass weight (Figure A.3) in our data. High grain and oilseed prices between 2006 and 2008 increased the cost of production for beef cattle producers. Beef cattle producers can respond to high feed ingredient costs by adjusting the types and amount of ingredients in feed rations, and the length of time spent in the feedlot, which in return can affect the quality grade of slaughter cattle. Other factors, such as age at slaughter and the type of breed, can explain variations in carcass characteristics by season and over time (Gray *et al.* 2012). These seasonal variations in carcass characteristics can influence the graders' judgement and serve as one of the potential sources of grader bias in beef carcass grading.

Figure A.1 shows that average Choice-Select spread in 2008 (5.31$/cwt) was less than those in 2005, 2006, and 2007 (9.33$/cwt, 13.81$/cwt, and 9.73$/cwt, respectively) indicating lower demand for higher quality beef in 2008, the period that overlaps with global financial crisis. During the economic recession, the demand for Choice beef declined as shown by the decrease in the Choice-Select spread (Figure A.1). Changes in demand may influence USDA graders and lead to calling less Choice. The entire sample, thus, is separated into two subsamples (before and during the crisis) to analyze the potential impact of the economic recession on grading behavior.

As shown in Table 2.2, the interval for Choice during the crisis, [5.04, 8.47), was significantly narrower than the one before the crisis, [4.20, 8.28). Both the lower and upper cutoff points during the crisis were significantly higher than the cutoff points before the crisis. The estimation results also show that the estimated cutoff points for each quality grade, 3.93, 5.04, and 8.47, were close to the USDA standards, 4.00, 5.00, and 8.00, after the crisis broke out. These results indicate that the USDA graders were more precise and careful when grading. Their possible awareness of higher demand for cheaper beef cuts during the recession might have influenced their grading. It is possible that USDA graders were trying to avoid grading errors to prevent giving financial advantages/disadvantages to either producers or packers.

2.4.3 Premiums and Discounts Analysis[7]

The trend in premiums and discounts for each quality grade during our sample period is illustrated in Figure A.4. The data were collected from USDA-AMS 5-Area Weekly Direct Slaughter Reports for the period covered in our data. The premiums and discounts for Choice are zero, since it serves as a base quality grade from which premiums and discounts are added/subtracted for Prime, Select, and Standard[8]. In 2008, premiums for Prime decreased, and discounts for Select and Standard also decreased (Figure A.4). This means that the premium-discount spread between Prime and Select as well as Prime and Standard became narrower. Because the change in premiums and discounts relates to consumer preferences and because packers send signals to producers about the quality of beef demanded through premiums and discounts[9], the narrow spread in 2008 implies that consumers preferred less expensive beef instead of high-quality beef as their income declined.

Our quality grade data includes weights of each beef carcass. Using weekly weighted averages of premiums and discounts provided by the USDA and 'camera-graded' and 'called' quality grades along with the weight of each carcass from our dataset, we were able to calculate the premiums and discounts of 'camera-graded' and

[7] Financial terms (loss/gain) in this analysis are used to express the amount of money that producers or packers would have earned if USDA human graders had been replaced by camera-grading system during the research period and do not have any normative meanings.

[8] Choice as the par value without premium or discount represents all Choices and does not account for high Choice which may have a premium in some grid pricing scales.

[9] If there is a market for high quality beef, then packers penalize more heavily the low-quality beef carcasses, while the premiums for high quality beef increase. However, when there is high demand for beef in general, then packers do not consider beef quality and decrease (increase) premiums (discounts).

‘called’ quality grade for each carcass. The difference in ‘camera-graded’ and ‘called’ quality grade premiums and discounts indicates how much producers or packers would have financially gained or lost if USDA graders were to be replaced by cameras during our sample period. By measuring this difference, we can forecast how replacing human graders with cameras may influence the future earnings of producers and packers. For example, if ‘camera-graded’ quality grade discounts were greater than ‘called’ quality grade discounts, the difference of the discounts provides the amount of money that producers or packers may lose if USDA graders were replaced by cameras. Although the amount of money that producers or packers could have lost is not identical with what they will lose in the future, we could roughly estimate the financial impact of the replacement on producers and packers. However, in the analysis we do not account for the dynamics of the market. If the volume of beef is changed by the full adoption of cameras, then the premium or discount of beef carcass may be altered. Because we do not account for this change in the analysis, the findings of this section need to be interpreted with caution.

Cattle are marketed mainly by three pricing methods: 1) live weight pricing, 2) dressed weight pricing, or 3) grid pricing (Schroeder and Davis, 1998). When slaughter cattle are priced on a live or dressed weight basis, packers and producers negotiate prices based on the expected value of the cattle. The expected value is determined by expected quality and yield grade, weight premiums and discounts, by-products, slaughter costs (sellers generally pay transportation on dressed cattle sales), and the packer’s profit. Since packers pay before cattle are graded by the USDA graders, packers can have financial gains if beef carcasses are graded at a higher quality grade than their expected value, and vice versa. Hence, under live and dressed weight pricing methods, only packers' earnings are influenced by the 'called' quality grade. When slaughter cattle are marketed based on yield and quality grade, i.e. grid pricing, price is based on the 'called' grade of each animal. Under grid pricing, the quality grade and yield grade influence producers' earning unlike live and dressed weight pricing. Therefore, under grid pricing, producers will lose financially when USDA graders call a lower quality grade than the true grade. In the case of the live and dressed weight pricing, packers will lose when USDA graders call a lower quality grade than the expected value for which they paid. Information on pricing method used for each carcass and expected value of cattle was unavailable to us, so we were not able to calculate the amount of money that each producer and each packer would gain or lose under different pricing methods. We, however, were able to calculate the combined financial gains/losses of producers and packers after replacing human graders with cameras by calculating the difference between 'called' and 'camera-graded' quality grade premiums and discounts. The expected value of the cattle did not affect the calculated difference, since the expected values of 'camera-graded' and 'called' quality grades were identical for each cattle carcass and cancel out when the difference is calculated.

The differences reported in Table 2.5 were calculated by subtracting the sum of 'called' quality grade premiums and discounts from the sum of 'camera-graded' quality grade premiums and discounts. The average difference in value of -$3.00/cwt is the amount of money producers and packers would have jointly lost on average per hundredweight of carcass if a camera grading system would have been used instead of USDA graders during our sample period.

Table 2.5. Premiums and Discounts of Camera-graded and Called Quality Grade

		Premiums and Discounts 'Camera-graded' Quality Grade (A)		Premiums and Discounts 'Called' Quality Grade (B)		Difference (A-B)	
Year	'Called' Quality Grade	Sum	Ave.	Sum	Ave.	Sum	Ave.
2005	Prime	235	3.4	760	11.0	-525	-7.6
	Choice	-7,124	-4.3	0	0.0	-7,124	-4.3
	Select	-8,310	-12.9	-4,274	-6.7	-4,036	-6.3
	Standard	-327	-10.9	-339	-11.3	11	0.4
	Total	-15,527	-6.4	-3,853	-1.6	-11,674	-4.8
2006	Prime	435	2.4	2,080	11.6	-1,645	-9.1
	Choice	-32,408	-7.3	0	0.0	-32,408	-7.3
	Select	-25,490	-15.8	-21,376	-13.2	-4,114	-2.5
	Standard	-951	-18.3	-951	-18.3	0	0.0
	Total	-58,413	-9.3	-20,246	-3.2	-38,167	-6.1
2007	Prime	553	6.3	1,182	13.4	-629	-7.1
	Choice	-4,895	-1.2	0	0.0	-4,895	-1.2
	Select	-13,318	-6.9	-14,296	-7.4	977	0.5
	Standard	0	0.0	0	0.0	0	0.0
	Total	-17,660	-2.9	-13,114	-2.1	-4,546	-0.7
2008	Prime	454	7.8	601	10.4	-147	-2.5
	Choice	-98	0.0	0	0.0	-98	0.0
	Select	-1,838	-2.6	-2,579	-3.6	741	1.0
	Standard	0	0.0	0	0.0	0	0.0
	Total	-1,482	-0.5	-1,978	-0.6	496	0.2
Total	Prime	1,677	4.2	4,623	11.7	-2,946	-7.5
	Choice	-44,524	-3.5	0	0.0	-44,524	-3.5
	Select	-48,956	-10.0	-42,524	-8.7	-6,431	-1.3
	Standard	-1,278	-15.6	-1,290	-15.7	11	0.1
	Total	-93,082	-5.1	-39,191	-2.2	-53,891	-3.0

Source: The quality grade data were collected from a large-scale Midwest packing plant; Premiums and discounts data were collected from USDA AMS National Weekly Direct Slaughter Cattle – Premiums and Discounts Report from May 2005 to October 2008.
Note: Sum (the average values) of premiums and discounts are reported in thousand dollars (dollars per hundredweight, $/cwt).

Traditionally, live weight pricing was very popular. However, over the past two decades dressed weight pricing and grid pricing methods became increasingly popular. According to the USDA report, over 50% of cattle sold during the period covered in our data were sold on grid pricing. Specifically, 56.3% (in 2005), 53.3% (in 2006), 57.2% (in 2007), and 62.3% (in 2008) of cattle were sold based on grid pricing (USDA 2014). To calculate and interpret the change in the earnings of producers and packers, respectively, we assume that the proportion of the grid pricing in our sample is similar to the national level. Hence, the combined difference of -\$53,981, as reported in Table 2.5, can be separated into producers' and packers' differences, -\$29,825 and -\$24,156, respectively. The difference of -\$29,825 for producers implies that producers will lose financially when the number of USDA graders is reduced through increased use of the camera grading system under grid pricing. The difference for packers (-\$24,156) implies that under dressed weight pricing, packers gain from grades called by USDA graders instead of camera grades. Here we are only considering transactions between producers and packers. In reality, the process is more complex and depends on how packers profitably market high- and low-quality carcasses in the wholesale market. The discount for low quality carcass can be high if packers have difficulty profitably marketing low quality beef. At the same time, packers may pay high premiums for high quality carcasses if there is a demand for high quality beef. Our results from Table 2.5 imply that on average packers were penalized more for low quality carcasses. The discounts for 'camera-graded' and 'called' grades for Standard, on average, were \$15.6/cwt and \$15.7/cwt, respectively, while the premiums for 'camera-graded' and 'called' grades for

Prime were $4.2/cwt and $11.7/cwt, respectively. Both ‘called’ and ‘camera-graded’ quality grade discounts for Standard were very similar to the national averages reported in Table 2.1. Whereas, ‘called’ and ‘camera-graded’ grade premiums for Prime were well below the national average.

Our results in this section are consistent with our findings in previous sections that the USDA graders were more generous in grading than the cameras. Since the USDA is working on reducing human graders, this might imply that producers and packers will lose financially if more cameras are used in grading.

Table 2.5 also shows that the difference in premiums and discounts has noticeably decreased after 2007. This result is consistent with our findings of annual data analysis. We found that, after the financial crisis started, USDA graders became much more precise and stricter in grading, and, at the same time, as illustrated in Figure A.4, both premiums and discounts decreased. These changes could be one of the reasons why the difference decreased after 2007.

2.5 Conclusions

The role of USDA graders is crucial in cattle and beef markets. Although USDA graders are well trained, a subjective determination of quality grades could cause grading errors. This study uses a unique data set and provides a comprehensive analysis of existence and possible sources of grader bias in assigning quality grades to beef carcasses and adds to the existing body of research that has addressed this issue.

The analyses in this paper used data from a large-scale Midwest packing plant. The data includes ‘called’ and ‘camera-graded’ quality grades for each beef carcass from May 2005 to October 2008. We also used the USDA reported weekly weighted averages of premiums and discounts for each quality grade along with ‘called’ and ‘camera-graded’ quality grades to estimate the financial impact of the reduced use of USDA graders and adoption of a camera grading system on beef cattle producers and packers.

The results of the interval estimation analysis indicate that USDA graders’ called grades were noticeably different from those measured by the camera grading system. The analyses suggest that seasonality in Choice-Select spread, consumer demand, number of carcass processed, and carcass characteristics can influence grading behavior of human graders. We also observed a central tendency bias in the grading behavior of USDA graders.

Our results have important implications for the current debate surrounding the wide-spread adoption of camera grading systems at packing plants. After verifying the existence of systematic grader bias across time, we investigated the possible impact of using camera grading methods instead of USDA graders on the economic gains/losses of producers and packers. When grading errors are systematically biased, the reduction of USDA graders’ utilization can influence the financial rewards of producers and packers. The results of the premiums and discounts analysis support the findings of the interval estimation analysis and show that combined earnings of producers and packers will decline when more camera grading is utilized in the beef grading system. Under grid pricing, producers will lose financially if camera grading is used instead of the USDA graders.

There are a number of limitations to the present work. First, in this paper we used data from 2005 through 2008. Conducting the analysis using newer data that was collected using more recent computerized technology in grading beef carcasses would provide more up to date information on beef grading and presence of grading errors. Second, we focused on investigating the financial impact of the USDA graders' replacement with cameras on packers and producers. The calculations were done without accounting for market response to changes in relative shares of different grades, hence the results provided in this paper need to be interpreted with caution. Third, it is also important to examine the welfare impact of the policy change on consumers. According to our results, we expect that beef prices will change when USDA graders are replaced by cameras. This price change will influence consumers' welfare in one way or another. Due to the lack of price information, it was not feasible to inspect this impact in this study. Hence, future research that focuses on using more recent data and more nationally representative samples in comparing 'called' and 'camera-graded' beef carcass grades is needed. Nonetheless, the findings of this study are relevant to a variety of policy questions.

3. ESTIMATING YIELD GRADING BIAS: A NON-PARAMETRIC APPROACH

3.1 Introduction

The U.S. Department of Agriculture (USDA) has worked on improving the reliability of the beef grading system. One of the UDSA's efforts is introducing instrument grading systems measuring yield index and marbling score, to improve the accuracy and consistency of beef grading (Woerner, and Belk 2008). In 2005, the USDA approved the use of instrument grading systems in packing plants. Nine packing plants introduced the instrument system to assist in their grading, and about 40 percent of the U.S. beef carcasses are graded by these systems daily (USDA 2013). The USDA further established a plan to expand the use of the instrument grading systems (USDA 2013). Following this series of USDA's efforts, animal scientists and agricultural economists analyzed evidence of the effectiveness of the instrument grading systems (Cross et al. 1983; Moore et al. 2010; Mafi, Harsh, and Scanga 2013). To the best of our knowledge, however, there are a few studies on the accuracy of the human yield grading system (Hueth, Marcoul, and Lawrence 2007; Jang et al. 2017). We fill this gap in this literature by examining the existence of grading bias in the human grading system.

The U.S. beef grading system was introduced to facilitate beef marketing and promote beef quality in 1926. The system makes communication easier among producers, packers, beef consumers in the U.S. beef industry. However, graders' inaccurate grading undermines the merits of the beef grading system. The existence of grading errors diminishes producers' incentives to produce better quality products (Chalfant and Rexton 2003) and hampers the effectiveness of the marketing process.

Even well-trained graders generate grading errors because they are calling grades within a few seconds based on their instant visual inspection of the beef carcass. Hueth, Marcoul, and Lawrence (2007) argue that such presence of grading errors is tolerable unless the errors are systematically biased across time and locations. If grading is inconsistent across time and locations, the reliability of the system will be compromised, and producers will no longer participate in the system.

In 1978, the U.S. Government Accountability Office (GAO) found different error rates in carcass grading across packing plants and recommended the USDA developing instrument grading systems to enhance the accuracy and consistency across regions. Hueth, Marcoul, and Lawrence (2007) proposed behavior models and defined grader bias as the systematical distinction between the distributions of "called" (grades assigned by USDA graders) and "true" (grades assigned according to the USDA standards[10]) yield grades. They also documented the presence of the bias in assigning yield grades. Mafi, Harsh, and Scanga (2013) compared marbling scores graded by experts, USDA human graders, and instrument grading systems, showing that the instrument grading systems are more precise and consistent than USDA human graders and reduce variations across plants.

[10] The USDA introduced and has updated the *United States Standards for Grades of Carcass Beef* (USDA 2017) that segregated beef carcasses into uniform groups, each of which has similar quality and composition.

The “grading bias” in this literature is defined as the systematical difference between the USDA standards and USDA graders’ implicit cutoff points between each grade. Based on this definition, the existence of grading bias is identified by estimating the graders’ implicit cutoff points from human-graded and instrument-graded yield grades and comparing these to the standard USDA cutoff points. Furthermore, a non-parametric behavioral model is used to estimate the cutoff point for each yield grade allowing relaxation of the normal distribution. Using this definition and approach, we investigate the existence of grading bias. If grading errors vary across time with the same USDA standards, we may be able to conjecture that external factors influence grading behavior. Hueth, Marcoul, and Lawrence (2007) discussed four potential sources of the bias – graders’ perception biases, pressure from packing plant staff or cattle producers, the lack of graders’ training, and corruption biases. However, they did not conclude what factors indeed influenced grader biases. Motivated by this, we attempt to reveal potential sources of the grader bias through comparing the pattern of grading bias across time.

The USDA beef grading system consists of quality and yield grades, which represent palatability and cutability, respectively. The physiological maturity and marbling of a beef carcass determine the quality grade, whereas hot carcass weight and fat thickness are the main determinants of yield grade (Field 2007). Quality grades are the well-known Prime, Choice, and Select quality grades and represent a measure of palatability from degree of marbling. Yield grades represent cutability of the carcass as measured by external fat and ribeye area. Both grades are the main elements of the USDA beef grading system, but their meanings and measurement methods are very different from each other. In this aspect, the concurrent analysis of both grades would make the discussion redundant and unnecessarily complicated. Thus, this research concentrates on yield grade in order to simplify the examination.

3.2 USDA yield grade

According to the USDA Standards (1997), yield grade is determined by yield index, which derived from the following prediction equation:

(4) Yield index (y) = 2.5 + 2.5 fat thickness + 0.2 kph + 0.0038 weight – 0.32 ribeye area

where kph refers to kidney, pelvic, and heart fat. The prediction equation was proposed by Murphy et al. (1960) and has been used since 1965. The weights placed on explanatory variables in Equation (4) convey that the main determinants of yield index (grade) are fat thickness and ribeye area. As external fat over the outside of the 12^{th} ribeye is thinner and ribeye area at the 12^{th} rib is wider, the yield index of a carcass becomes smaller and better. The USDA yield grade consists of five grades: yield grade 1 (best) through 5 (worst). For instance, if the yield index is strictly less than 2.00 or greater than 4.99, the yield grade is 1 or 5. If the yield index is in the range of 2.00-2.99, 3.00-3.99, or 4.00-4.99, then the yield grade is 2, 3, or 4, respectively.

Graders are hired and trained by the USDA and provide grading services in packing plants at the voluntary request of packers. Graders are trained for two years before they can start issuing unsupervised calls, and their performance is regularly monitored and supervised by their seniors and peers to maintain grading accuracy and consistency. Nonetheless, a time-constrained visual inspection process leads to assessing a carcass based on personal experience and knowledge earned from their training sessions, rather than the prediction equation alone. This type of grading practice in commercial packing plants may suggest the existence of subjectivity in human-graded yield grades.

The valuation criteria of each yield grade are expressed as an index derived from the prediction equation. With the use of instrument grading systems, the weight and kph of a carcass are measured by a scale, and fat thickness and ribeye area are measured by a video analysis system. The indexed criteria based on the prediction equation indicate that yield grades assessed by instruments are accurate and consistent. Furthermore, animal scientists have shown that the visual analysis system improves the accuracy and consistency in the estimation of carcass yield characteristics (Cross et al. 1983; George et al. 1996; Steiner et al. 2003). Based on this, we assume that instrument-graded yield grades are true grades defined by the USDA standards. Under this assumption, we develop a non-parametric estimation model to estimate a cutoff point for each yield grade.

3.3 Model

As illustrated in Figure A.5, the density functions indicate that the conditional distributions of yield grade 1 and 5 do not follow a normal distribution. Equality tests also indicate that the distributions of yield grades 1 and 5 do not match a normal distribution. P-values from the tests between the normal and the two conditional distributions produced are less than 0.01, which reject the null hypothesis that they have identical distributions. A non-normal distribution indicates cutoff points estimated with the normal distribution would be likely to be biased. Given this fining, a non-parametric approach to estimate consistent cutoff points with the non-normality was adapted.

Let $\mathrm{I_k}$ represent the yield index interval of yield grade k. The process of calling yield grade can be expressed as the following function:

(5) Yield Grade = {k | Yield Index $\in \mathrm{I_k}$, k = 1, 2, 3, 4, and 5}.

According to the USDA standards (1997), USDA yield index intervals ($\hat{\mathrm{I}}_\mathrm{k}$) for each yield grade are: $\hat{\mathrm{I}}_1 = (-\infty,\ 2.0)$, $\hat{\mathrm{I}}_2 = [2.0, 3.0)$, $\hat{\mathrm{I}}_3 = [3.0, 4.0)$, $\hat{\mathrm{I}}_4 = [4.0, 5.0)$, and $\hat{\mathrm{I}}_5 = [5.0,\ +\infty)$. Graders should call yield grade 1 when the observed yield index falls within the yield index interval of yield grade 1 ($\hat{\mathrm{I}}_1$). Other yield grades should be called in a similar way.

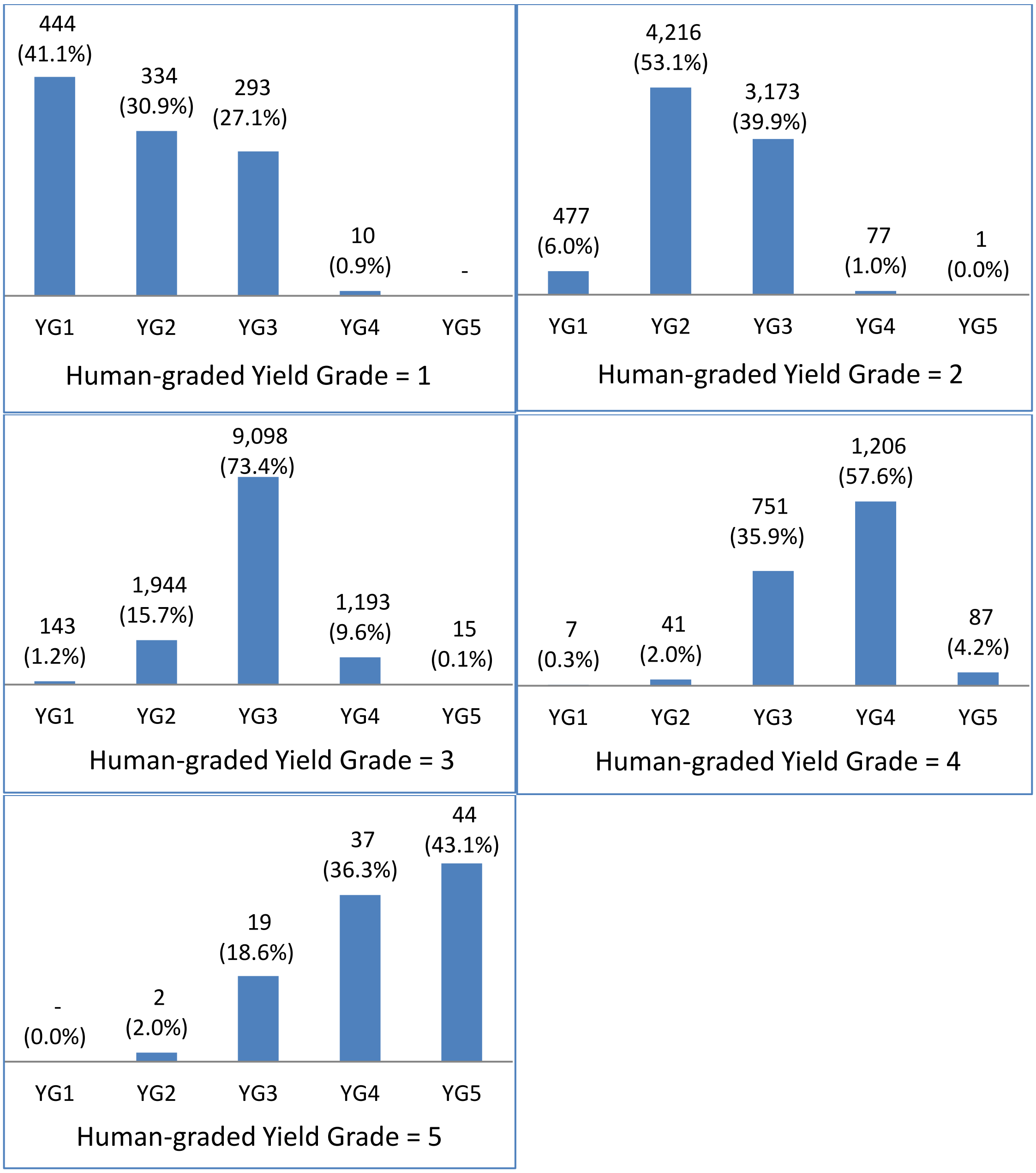
As shown in Figures 3.2 and 3.3, a human-graded yield grade was not identical to an instrument-graded yield grade. The difference indicates that human graders' yield index intervals ($\tilde{\mathrm{I}}_\mathrm{k}$) can be different from USDA yield index intervals ($\hat{\mathrm{I}}_\mathrm{k}$). Given this finding, human graders' yield index intervals ($\tilde{\mathrm{I}}_\mathrm{k}$) were defined with their own implicit cutoff points($\mathrm{C_k}, \mathrm{k} = 1,\ 2,\ 3,\ \text{and } 4$), $\tilde{\mathrm{I}}_1 = (-\infty, \mathrm{C}_1),\ \tilde{\mathrm{I}}_2 = [\mathrm{C}_1,\ \mathrm{C}_2),\ \tilde{\mathrm{I}}_3 = [\mathrm{C}_2,\ \mathrm{C}_3)$, $\tilde{\mathrm{I}}_4 = [\mathrm{C}_3,\ \mathrm{C}_4),\ \tilde{\mathrm{I}}_5 = [\mathrm{C}_4,\ +\infty)$. If human graders' implicit cutoff points differ from the USDA cutoff points, it will indicate the existence of systemically biased grading errors.

Let h_i be a human-graded yield grade and m_i be an instrument-graded yield grade for a carcass i. Assuming that an yield index (y) is continuous then human graders maximize the probability of calling a true grade based on an observed yield index. A human grader calls a carcass as yield grade k when an observed yield index (y) is less than C_{k+1} and greater than or equal to C_k. Let $F_k(C_k)$ present the cumulative density function of a real-valued cutoff point C_k given a human-graded yield grade. Then we have equalities:

(6) Prob $\{y \leq C_{k+1} \mid h_i = k+1\} = F_{k+1}(C_{k+1})$,

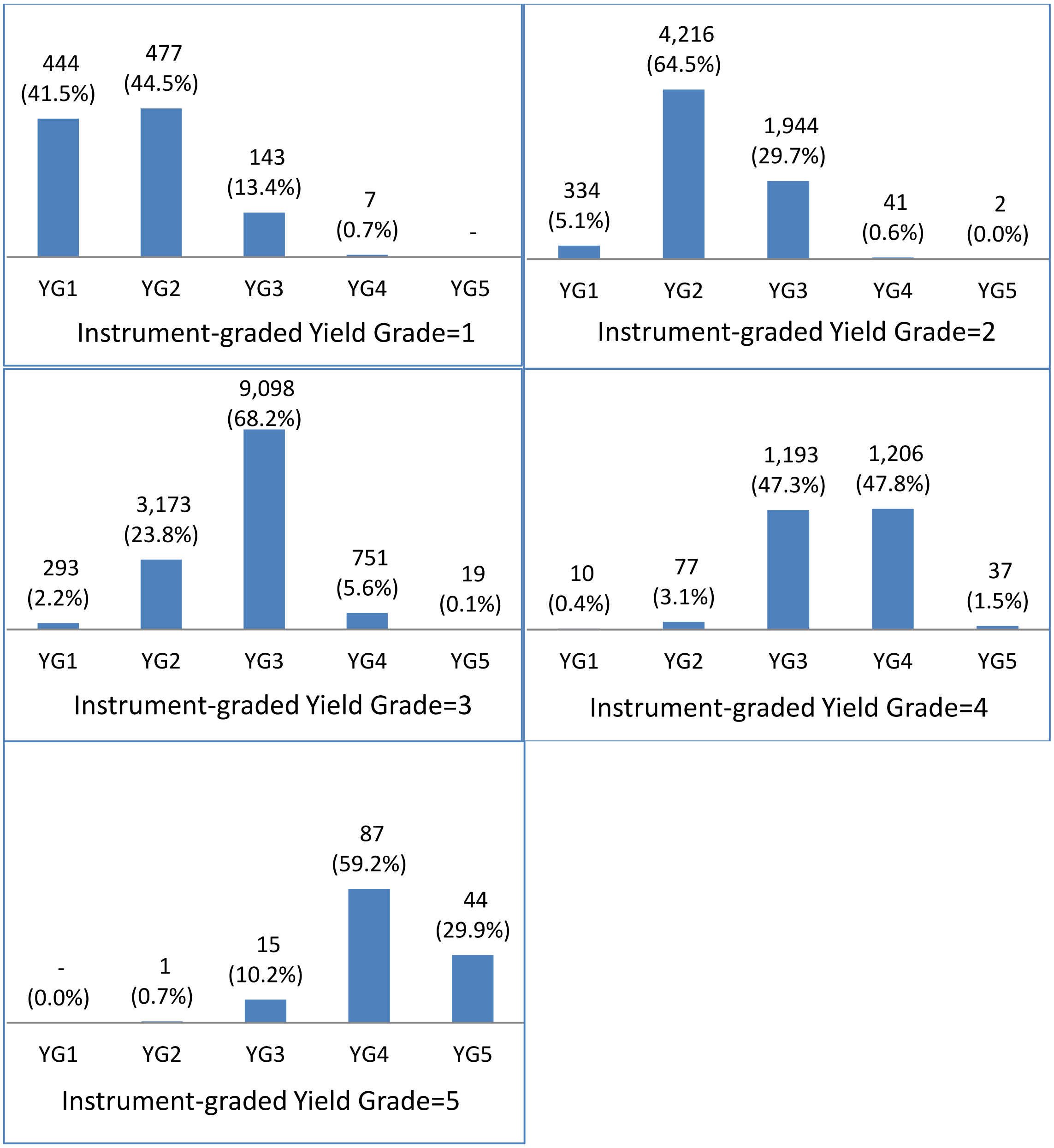
(7) Prob $\{y \leq C_k \mid h_i = k\} = F_k(C_k)$.

Given these equalities, the probability of calling a true grade given an instrument-graded grade for yield grade k is $F_{k+1}(C_k) - F_k(C_k)$. Maximizing this difference is identical to maximizing the probability of calling a true grade.



Source: The yield grade data were collected from a large-scale Midwest packing plant from May 2005 to October 2008.

Figure 3.1. The Conditional Distribution of Instrument-graded Yield Grade given Human-graded Yield Grade (the number of head, percent of total graded in parentheses)



Source: The yield grade data were collected from a large-scale Midwest packing plant from May 2005 to October 2008.

Figure 3.2. The Conditional Distribution of Human-graded Yield Grade given Instrument-graded Yield Grade (the number of head, percent of total graded in parentheses)

A kernel estimator was employed to estimate cumulative density functions involved in the above equations. Smoothed empirical cumulative density functions were used instead of theoretical ones (Fluss, Faraggi, and Reiser 2005). Following Nadaraya (1965), we defined the empirical cumulative density function as

(8) $$\tilde{F}_k(C_l) = \frac{1}{n_k} \sum_{i=1}^{n_k} \Omega_k\left(\frac{C_l - m_i}{b_k}\right) \text{ for k = 1, 2, 3, 4, and 5,}$$

where $\Omega_k(\,)$ is the Gaussian kernel function, and n_k is the number of observations graded as yield grade k. According to Silverman (1986), and Fluss, Faraggi, and Reiser (2005), the bandwidths, $b_k = 0.9 \min\left\{s_k, \frac{iqr_k}{1.34}\right\} n_k^{-0.2}$, k = 1, 2, 3, 4, and 5, were utilized for managing the amount of smoothing, where s_k and iqr_k are the standard deviation and the inter quartile range of the sample, respectively.

Based on the empirical cumulative density functions, a likelihood function that graders want to maximize is defined as follows:

(9) $$\begin{aligned} L(h_j, m_j \mid C_1, C_2, C_3, C_4) \\ &= \mathbf{1}(h_j = 1)\tilde{F}_1(C_1) \\ &\quad \times \prod_{k=1}^{3} \mathbf{1}(h_j = k)[\tilde{F}_{k+1}(C_{k+1}) - \tilde{F}_k(C_k)] \\ &\quad \times \mathbf{1}(h_j = 5)[1 - \tilde{F}_5(C_4)], \end{aligned}$$

where, C_k, k $\in \{1, 2, 3, 4\}$ are parameters to be estimated, **1** ( ) is an indicator function, and F_j( ), j = 1, 2, 3, 4, and 5, is an empirical cumulative density function for each yield grade. Like previous research work suggesting new non-parametric models (Li, and Racine 2003; Fluss, Faraggi, and Reiser 2005; Pablo 2011), simulation studies were conducted to assure the consistency of the suggested non-parametric behavior model before applying the model to real data analysis.

3.4 Simulation Studies

Medical scientists have developed non-parametric cutoff point estimation models to identify an accurate threshold employed in a physician's decision. They documented that a non-parametric model performed better with non-normal data than parametric models (Pablo 2011; Nakas et al. 2012). To the best of our knowledge, this article is the first attempt to employ a non-parametric method to estimate multiple cutoff points in beef grading. Estimated cutoff points using this new model were compared with predetermined true cutoff points to show the consistency of the proposed behavior model. Pre-generated data with the known means and standard deviations allowed us to calculate true cutoff points for each grade.

3.4.1 Sample Data Generation

Two distinct data sets, which follow the normal and non-normal distribution, respectively, were generated to carry out simulation studies. In the first dataset, the data of each yield grade following the normal distribution with the fixed mean (k+0.5 for k=1, 2, 3, 4, 5) and standard deviation (0.5) were generated. Given these predetermined distributions, true cutoff points for each yield grade were calculated as 2, 3, 4, and 5 for yield grades 1 to 5.

In the second dataset, the yield grade 5 data follow the lognormal distribution, LN (7.5, 0.6), while the data for other yield grades follow the normal distribution, N (k+0.5, 0.5) for k= 2, 3, 4, and 5, just like the first data set. Given these distributions, true cutoff points are 2, 3, 4, and 6 for grade 1 to 5. Due to the right skewed lognormal distribution, the true cutoff point (6.0) between yield grade 4 and 5 is larger than that for the first dataset (5.0). We selected yield grade 5 as the grade following the non-normal distribution, because, as shown in Figure A.5, the actual conditional distribution of yield grade 5 follows a right skewed distribution. The second dataset was generated to evaluate the performance of the model with non-normal data. If estimated cutoff points from the two datasets are statistically identical to the true ones, we can conclude that the proposed model produces a consistent estimator with both normal and non-normal data.

It is well-documented that with a small sample size a non-parametric method does not work well. Hence, the estimation is carried for different sample sizes (100, 1,000, and 5,000 for each yield grade) to assess the influence of the sample size on the non-parametric estimation. Estimated cutoff points using a parametric model are compare to those estimated from the non-parametric model. This comparison shows whether the non-parametric model outperforms a model with the non-normal distribution.

3.4.2 The Results of Simulation Studies

The simulation results ($\mathrm{n_k} = 5{,}000$) with the non-parametric model in Table 3.1 present that estimated cutoff points (1.99, 3.01, 4.00 and 5.01) are statistically identical with the true ones (2.00, 3.00, 4.00, and 5.00). The Wald test for testing the null hypothesis: $C_1 = 2.00, \mathrm{C}_2 = 3.00, \mathrm{C}_3 = 4.00,\ \text{ and } \mathrm{C}_4 = 5.00$ indicates failure to reject the hypothesis (Table 3.2). In addition, the results with the parametric model show that estimated cutoff points are consistently close to the true ones. This means that both parametric and non-parametric behavior models produce unbiased estimation results when the sample data are generated from the normal distribution.

Table 3.1 indicates that the nonparametric behavioral model performs better than the parametric model when the data follow a non-normal distribution. The estimated cutoff point ($\hat{\mathrm{C}}_4 = 5.75, \mathrm{n_k} = 5{,}000$) between grade 4 and 5 of the nonparametric model is statistically identical with the true one (6.00): the Wald test indicates the acceptance of the hypothesis ($C_4 = 6.00$), as shown in Table 3.2. This suggests that the distribution of the sample data influences the estimation result. In addition, the proposed non-parametric behavior model generates a consistent estimator even with the non-normal data.

Table 3.1. Simulation Results Testing Non-Parametric and Parametric Models of Cutoff Points

	n_k = 100 (k = 1, 2, 3, 4, 5)		n_k = 1,000 (k = 1, 2, 3, 4, 5)		n_k = 5,000 (k = 1, 2, 3, 4, 5)	
	Non-parametric model	Parametric model	Non-parametric model	Parametric model	Non-parametric model	Parametric model
(1) Simulation Results with Normal Distribution						
$\hat{C}_1$	1.953 (0.825)	1.953 (0.063)	1.986 (0.792)	1.974 (0.020)	1.988 (0.808)	1.970 (0.010)
$\hat{C}_2$	2.864 (1.060)	2.991 (0.060)	3.037 (0.803)	3.000 (0.018)	3.011 (0.701)	2.998 (0.008)
$\hat{C}_3$	4.066 (0.738)	4.007 (0.059)	4.055 (0.677)	4.006 (0.018)	3.997 (0.775)	4.001 (0.009)
$\hat{C}_4$	5.047 (1.633)	5.045 (0.065)	5.001 (0.703)	5.030 (0.020)	5.012 (0.744)	5.030 (0.010)
Ln L	3.5	-333.8	3.7	-3,213.5	3.7	-20.452.5
(2) Simulation Results with Lognormal Distribution						
$\hat{C}_1$	2.022 (0.672)	1.969 (0.059)	2.070 (0.861)	1.974 (0.020)	2.005 (0.740)	1.969 (0.009)
$\hat{C}_2$	2.973 (0.635)	3.005 (0.057)	3.005 (0.717)	3.000 (0.018)	2.984 (0.706)	2.998 (0.008)
$\hat{C}_3$	4.112 (0.663)	4.022 (0.056)	3.972 (0.694)	4.009 (0.019)	3.992 (0.690)	4.005 (0.009)
$\hat{C}_4$	5.759 (1.449)	5.150 (0.083)	5.737 (1.541)	5.127 (0.027)	5.754 (1.679)	5.110 (0.012)
Ln L	4.0	-258.3	4.0	2,714.8	4.0	-13,998.6

Note: Standard errors in parentheses; All the estimated parameters were significant at 5% level; n_k represents the number of observations for each yield grade; $\hat{C}_k$ for k = 1, 2, 3, and 4, is an estimated cutoff point for each yield grade and is defined in the equation (9).

Table 3.2. Wald and Profile Likelihood (PL) Confidence Limits for Null Hypothesis ($C_1 = 2.00, C_2 = 3.00, C_3 = 4.00,$ and $C_4 = 5.00$ (or 6.00))

Null Hypothesis	Estimate	Wald Confidence Limits	
		Lower Limit	Upper Limit
(1) Simulation with Normal Distribution			
C_1 = 2	1.988 (0.808)	1.443	2.533
C_2 = *3*	3.011 (0.701)	2.538	3.484
C_3 = 4	3.997 (0.775)	3.475	4.520
C_4 = 5	5.012 (0.744)	4.510	5.514
(2) Simulation with Lognormal Distribution			
C_1 = 2	2.005 (0.740)	0.980	3.030
C_2 = 3	2.984 (0.706)	2.005	3.962
C_3 = 4	3.992 (0.690)	3.036	4.948
C_4 = 6	5.754 (1.679)	3.427	8.081

Note: C_k for k = 1, 2, 3, and 4, is a cutoff point for each yield grade and is defined in the equation (9).

3.5 Data

Table 3.3 summarizes the 23,612 graded beef carcasses which were collected from a large-scale Midwest packing plant for the period May 2005 through August 2008. Two distinctive yield grades, human-graded and instrument-graded grades, for an identical beef carcass were used to identify the patterns of grading errors across yield grades. Comparative analyses were performed across time using date processed and carcass traits for each carcass, along with yield grades.

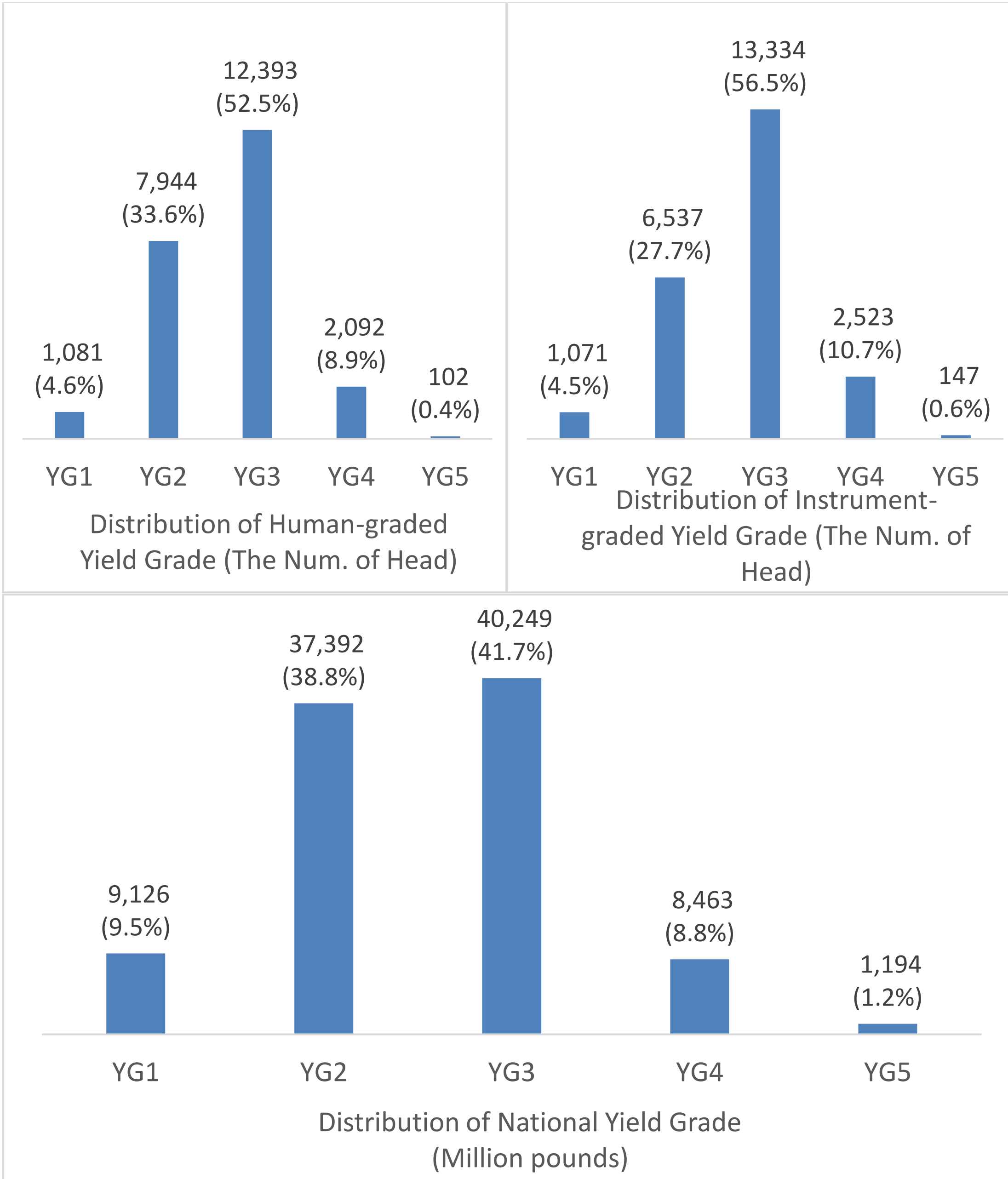
The data contained in Figures 3.2 is the instrument graded yield grade conditional to the human graded yield. The numbers in the figure reflect the percentage of grading errors, for example, the human grader called a carcass yield grade 1 and the instrument graded the same carcass yield grades 1 – 5. For example, when the human grader called a carcass yield grade 1, the instrument graded, or called the same grade in 41.1% of carcasses. The histograms in Figure 3.1 illustrates the existence of grading errors across yield grades. The accuracy rates are less than 60.0%, except for yield grade 3 (73.4%), In particular, the accuracy rates of yield grades 1 (41.1%) and 5 (43.1%) are relatively lower than those of yield grades 2 (53.1%) and 4 (57.6%). This pattern suggests that human graders had a tendency to generate more grading errors when they assess extreme grades, such as yield grades 1 and 5. Put differently, human graders tended to make less grading errors when they assessed the central grade, such as yield grade 3.

Table 3.3. Summary Statistics of Yield Index Carcass Data

Period	Num. of obs.	Mean	Std. Dev.
Whole Sample Period	23,612	3.25	0.69
Seasonal Analysis			
Spring (Mar - May)	9,382	3.31	0.67
Summer (Jun - Aug)	10,582	3.18	0.71
Fall (Sep - Nov)	2,500	3.22	0.65
Winter (Dec - Feb)	1,148	3.33	0.30
Weekend effect Analysis			
Weekday (Mon – Fri)	20,488	3.22	0.69
Weekend (Sat – Fri)	3,124	3.44	0.66
Financial Crisis Analysis			
Before (May 2005 – Jul 2007)	19,842	3.30	0.66
During (Aug 2007 –Oct 2008)	3,770	2.95	0.77
Corn Price Analysis (Break point: Jan 1, 2007)			
Before (May 1, 2005 – Jan 1, 2007)	14,103	3.35	0.61
After (Jan 2, 2007 – Oct 31, 2008)	9,509	3.10	0.77
Feed Ratio Analysis (Break point: Nov 1, 2006)			
Before (May 1, 2005 – Nov 1, 2006)	13,751	3.35	0.60
After (Nov 1, 2006 – Oct 31, 2008)	9,861	3.10	0.77
Workload Analysis			
May - August	16,412	3.22	0.70
Other months	7,200	3.31	0.64

Source: The yield index data were collected from a large-scale Midwest packing plant from May 2005 to October 2008.

Note: Yield index represents the amount of edible meat from a beef carcass; According to the USDA standards (1997), USDA yield index intervals ($\hat{I}_k$) for each yield grade are: $\hat{I}_1 = (-\infty,\ 2.0)$, $\hat{I}_2 = [2.0, 3.0)$, $\hat{I}_3 = [3.0, 4.0)$, $\hat{I}_4 = [4.0, 5.0)$, and $\hat{I}_5 = [5.0,\ +\infty)$.



Source: The human graded and instrument graded yield grade data were collected from a large-scale Midwest packing plant from May 2005 to October 2008. National yield grade date were collected from AMS/USDA (http://www.ams.usda.gov/reports/meat-grading) from May 2005 to October 2008.

Figure 3.3. The Distribution of Human-graded, Instrument-graded, National Yield Grade (the number of head, percent of total graded in parentheses)

Furthermore, as illustrated in Figure 3.2, more than 50% of the carcasses were graded as yield grade 1 by human graders, even though instruments graded them as grade 2 or 3. Meanwhile, the carcasses were graded as yield grade 5 when instruments graded them as grade 3 or 4. This indicates that human graders tended to be more generous when they evaluated higher yield carcasses, while they tended to be stricter when they graded lower yield carcasses. In other words, graders had a tendency to overestimate specific positive traits of carcasses and underestimate certain negative traits of carcasses.

Although Figures 3.2 and 3.3 provide the patterns of grading errors across yield grades, it is still necessary to estimate graders' implicit cutoff points to look for the existence and potential sources of grading bias. The results in this section might suggest that estimated cutoff points of the extreme grades (yield grades 1 and 5) could be more severely biased than other yield grades, and that implicit cutoff points of these extreme grades would approach sub-centrally towards those of yield grade 3.

Figure 3.3 illustrates the distribution of human-graded yield grades is not identical with the one of instrument-graded yield grades. Both human graders and instruments evaluated most of the carcasses (humans: 86.1%, instruments: 84.2%) as yield grade 2 and 3. However, human graders called yield grade 2 more frequently than instruments, while they called yield grades 3 and 4 less than instruments. These differences suggest that human graders were more generous than the instruments.

The distribution of national yield grades issued by the National Summary of Meat Graded Reports in Figure 3.3 describes that most of the carcasses (80.5%) were graded as yield grades 2 and 3 during our sample years. The distributions of national and human-graded yield grades could not be identical, because the units of these two distributions are different: the unit of the human-graded yield grade is the number of head, while the unit of the instrument-graded yield grade is the total weight of processed carcasses (i.e., million pounds). Despite this unit difference, their distribution shapes are still similar. This indicates that the data used in this article represents the national level data.

3.6 Results

3.6.1 Existence of Grading Bias

Estimation results in Table 3.4 demonstrate that grading bias exists in U.S. beef yield grading across time. As indicated in the previous section, the estimated threshold between grades 1 and 2 is 2.27 (Table 3.4), which is greater than the USDA threshold of 2.00. Meanwhile, the estimated threshold between grades 4 and 5 is 4.69, which is less than the USDA threshold of 5.00. These results represent that USDA human graders tended to call yield grade 1 instead of grade 2 when yield index was greater than the USDA standard of 2.00, while they call yield grade 5 instead of grade 4 when yield index was less than the USDA standard of 5.00. This tendency corresponds with human graders' generosity against high yield carcasses and severity against low yield carcasses.

Human graders were more accurate when they evaluated carcasses of the central grade (grade 3) than those of extreme grades (grade 1 and 5). Figure 3.4 shows that the estimated interval of yield grade 3, [3.09, 3.86), is close to the USDA standard interval of [3.00, 4.00), whereas the estimated intervals of yield grade 1 and 5, (-∞, 2.26), and [4.69, +∞), are wider than those of the USDA standards, (-∞, 2.00), and [5.00, +∞). Human graders might tend to evaluate the central grade more accurately after being repeatedly exposed to assess the grades. As illustrated in Figure 3.3, 56.5% (13,334 heads) of total instrument-graded carcasses (23,612 heads) were graded as yield grade 3, whereas only 4.5% (1,071 heads), and 0.6% (147 heads) of the carcasses were graded as yield grades 1 and 5, respectively. A high proportion of central grades (yield grade 3) in the sample suggests that graders had more chances to see and evaluate central grades than extreme grades (yield grades 1 and 5). We conjectured that the high frequency of central grade evaluation would explain more accurate assessment of central grades than other extreme grades.

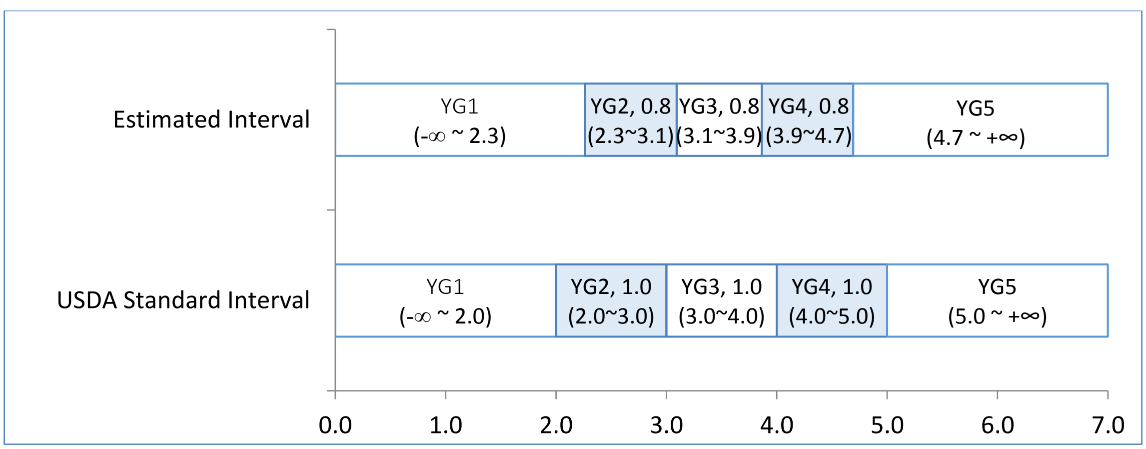


Figure 3.4. Estimated and USDA Standard Intervals: Whole Sample Analysis

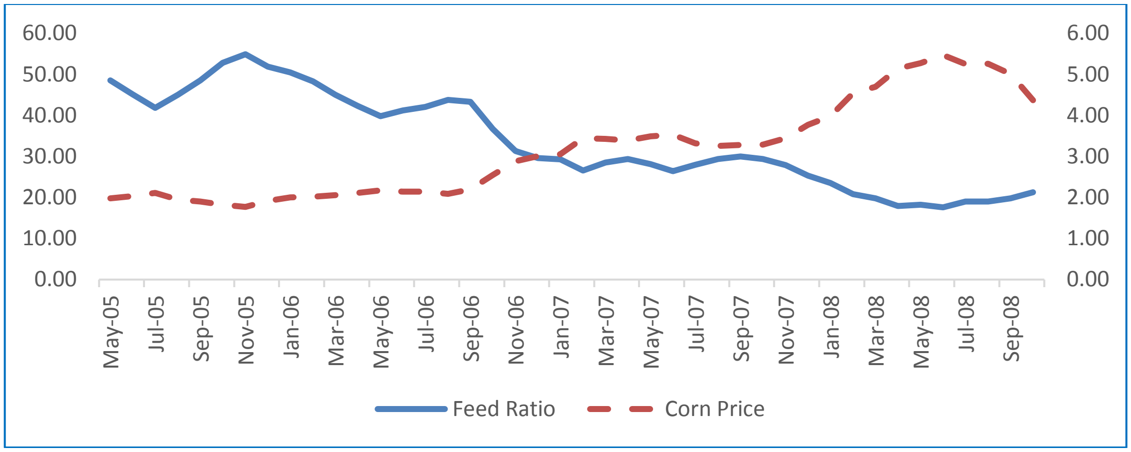
3.6.2 Weekend Effect in Beef Grading

Graders' perception biases might result in their grading biases. One of the cognitive biases that can be examined in this article is the weekend effect, which indicates a different pattern in human graders' behavior before, during, or after weekends compared to their behavior during workdays. Researchers in psychology, medical science, finance, and labor economics have investigated the weekend effect by comparing well-being indexes, mortality rates, stock returns, and productivity across weekdays and weekends, respectively, and found different behavior patterns between Monday and Friday (or weekends). The well-being of workers and students was higher during weekends than workdays (Ryan, Bernstein, and Brown 2010). Investors undervalued stocks on Monday compared to Friday (Donald, and Stambaugh 1984). The death rate on weekends was higher than one on weekdays (Schmulewitz, and Bell 2005). The productivity of labors varies across workdays. For instance, Bryson and Forth (2007) documented that the fewest errors were detected on Mondays at a German car manufacturing plant in 2003-2004. These findings imply the possibility of the existence of the weekend effect in U.S. beef grading, because USDA graders are (1) human beings that are influenced by their well-being or mood, (2) workers who regularly perform their tasks every weekday, and (3) graders who subjectively determine grades based on their visual inspection given the limited time. These features of graders led us to investigate the existence of the weekend effect in beef grading by comparing grading patterns across workdays.

Table 3.4 describes how grading behavior during weekdays (Monday - Friday) is different from the behavior over weekends (Saturday - Sunday). Implicit estimated cutoff points between grades 1 and 2 and between grades 3 and 4 (2.4, and 4.0) are lower to those during weekdays (2.2, and 3.8). These differences indicate that human graders were more generous graders during weekends compared to workdays. Increased well-being, extra pay, perhaps fewer cattle to grade on a weekend, or clean up shift might influence their grading behavior. The differences show the evidence of the weekend effect in beef grading.

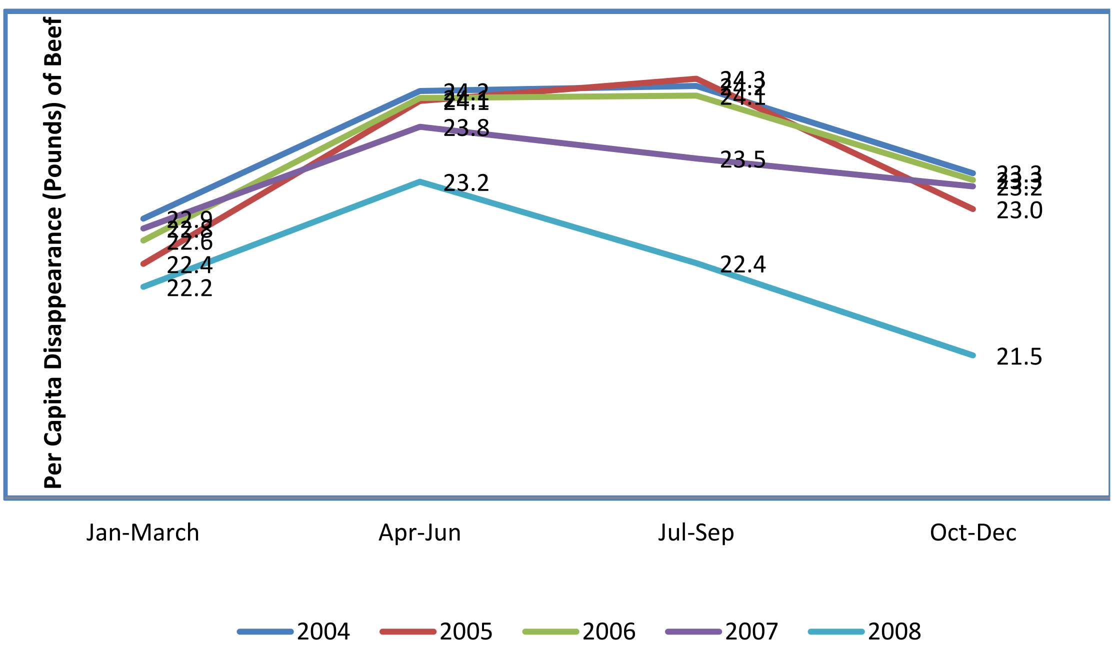
3.6.3 Variations in Corn Prices and Beef Consumption

Two economic events which reduced the profitability of producers and packers occurred during our sample period. Corn prices sharply surged from late 2006 through the first half of 2008, and the financial crisis began in 2007-2008. Figure 3.5 contains corn prices and the steer and heifer – corn ratio (steer and heifer price per cwt/corn price per bushel). Such decreases in the ratio indicates that producers' profitability declined due to higher feeding costs. Furthermore, beef (per capita disappearance) decreased in 2007 and 2008 (Figure 3.6). We analyzed the impact of these events on carcass grading because producers could respond more sensitively to grading when their profit margin become tight due to increased input costs and decreased beef consumption. The effect of variations in corn prices and beef consumption on beef grading behavior was examined by comparison analysis in grading patterns in this section.



Source: USDA ERS Grain Feed Data: Yearbook Tables (https://www.ers.usda.gov/data-products/feed-grains-database/feed-grains-yearbook-tables/)

Figure 3.5. Average Corn Price Received by Farmers (dollars per bushel) and Feed Price Ratio – Corn (percentage), May 2005 - October 2008



Source: USDA ERS Livestock & Meat Domestic Data (https://www.ers.usda.gov/data-products/livestock-meat-domestic-data/)

Figure 3.6. Beef Per Capita Disappearance, 2004 – 2008, Quarterly

First, break points were estimated, which separate high and low corn-steer price ratio periods using a breakpoint regression (Bai-Perron tests). The test results show that the estimated break points of the corn price and the feed ratio are January 2007 and November 2006, respectively. For the 2007-2008 financial crisis, we adopted the break point (August 2007) proposed by Guidolin and Tam (2011). These break points were used to estimate and compare the cutoff points before and after the reference dates.

Table 3.4 contains estimated human graders' cutoff point between grades 1 and 2 during pre and post-financial crisis period. The estimated human graders' cutoff point during the post-crisis period (2.02) was significantly less than the cutoff point during the pre-crisis period (2.31). Similar results are found from other breakpoint analyses of corn prices and the feed ratio. This shows that graders strictly evaluated beef carcasses during the crisis period. Graders might be consciously or unconsciously aware of the impact of their miscalls on producers' and packers' profitability when economy went into recession. They might recognize that peaked corn prices and decreases in beef consumption could be a burden to both producers and packers. When the economic condition is not in favor of producers and packers, graders may try not to make grading errors, which end up giving pecuniary benefit to one of those parties. Taken together, unfavorable economic conditions revealed the possibility that economic events influence producers' profitability could be the potential source of the grading bias.

3.6.4 Seasonality in Beef Carcass Traits and the Number of Processed Beef Cattle

Variations in the determinants of yield grade and the number of processed beef cattle could be the causes of grading biases. The determinants of yield grades are: (1) ribeye area, (2) hot carcass weight, (3) fat thickness, and (4) estimated percentage of kidney, pelvic, and heart fat (kph). Figure A.3 shows that these four determinants had seasonal trends during our sample period. There are seasonality effects on grades which could be attributed to seasonal trends in temperature, age of cattle fed, finishing weights of the feedlots. Several studies reveal that the performance and efficiency of livestock are affected by climatic conditions such as temperature and humidity (Young 1981, Birkelo, Johnson, Phetteplace 1991, and Piao and Baik, 2015). Likewise, the volume of processed slaughter cattle had a trend across months (Figure A.2). The number of cattle processed during the period of May through August was greater than during other months. Given seasonal influences, a seasonal effect on grading bias was explained by comparing estimated cutoff thresholds across seasons and months.

If graders were affected by the seasonality, then there should be difference in grade cutoffs from one season to the next. The results indicate that while human grader cutoffs did differ from the standard, there was little difference in cutoff between season. This indicates that the variation of beef carcass traits between seasons did not affect grading behavior.

Commercial chain speed in packing plants is 340 carcasses per hour (Steiner et al 2003). Increased cattle slaughter numbers in the May through August period is greater than for other months. The estimated cutoff points between the highest volume months and other months are similar to each other, as shown in Table 3.4. This suggests that an increment in the number of slaughtered carcasses did not result in increased biases in grading.

Table 3.4. Estimated Effect of Financial Crisis, Corn Prices and Other factors on Estimated Human Graded Yield Grades

Period	$\hat{C}_1$	$\hat{C}_2$	$\hat{C}_3$	$\hat{C}_4$	ln L
USDA Standards	2.000	3.000	4.000	5.000	
Whole Sample Estimation	2.266*** (0.835)	3.090*** (0.768)	3.860*** (0.636)	4.687*** (0.622)	103.8
Weekend effect Analysis					
Weekdays (Mon – Fri)	2.241*** (0.893)	3.074*** (0.775)	3.842*** (0.621)	4.684*** (0.655)	2.8
Weekend (Sat - Sun)	2.383*** (0.572)	3.197*** (0.640)	4.014*** (0.683)	4.693*** (0.598)	3.3
Financial Crisis Analysis (Break point: Aug 31, 2007)					
Before (May 2005 – Jul 2007)	2.312*** (0.082)	3.118*** (0.715)	3.881*** (0.604)	4.700*** (0.636)	91.8
During (Aug 2007 –Oct 2008)	2.023*** (0.720)	2.911*** (0.762)	3.639*** (0.726)	4.592*** (0.758)	14.0
Corn Price Analysis (Break point: Jan 1, 2007)					
Before (May 1, 2005 – Jan 1, 2007)	2.345*** (0.842)	3.151*** (0.731)	3.882*** (0.574)	4.690*** (0.642)	2,6
After (Jan 2, 2007 – Oct 31, 2008)	2.183*** (0.663)	3.022*** (0.600)	3.828*** (0.713)	4.700*** (0.558)	40,3

Note: Standard errors in parentheses; '***', '**', and '*' represent significance at 0.01, 0.05, and 0.1 levels, respectively. $\hat{C}_k$, k=1, 2, 3, and 4 is an estimated cutoff point for each yield grade and is defined in the equation (9).

Table 3.4. Continued

Period	$\hat{C}_1$	$\hat{C}_2$	$\hat{C}_3$	$\hat{C}_4$	ln L
USDA Standards	2.000	3.000	4.000	5.000	
Feed Ratio Analysis (Break point: Nov 1, 2006)					
Before (May 1, 2005 – Nov 1, 2006)	2.348*** (0.848)	3.155*** (0.744)	3.882*** (0.537)	4.691*** (0.648)	2,6
After (Nov 1, 2006 – Oct 31, 2008)	2.187*** (0.660)	3.024*** (0.603)	3.831*** (0.709)	4.697*** (0.552)	40,3
Seasonal Analysis					
Spring	2.301*** (0.755)	3.114*** (0.707)	3.855*** (0.573)	4.694*** (0.530)	53.0
Summer	2.258*** (0.853)	3.069*** (0.728)	3.875*** (0.735)	4.682*** (0.719)	40.8
Fall	2.203** (1.160)	3.097*** (0.842)	3.841*** (0.633)	4.573*** (1.032)	5.6
Winter	2.356** (1.199)	3.150** (1.615)	3.907*** (0.791)	4.675*** (0.976)	9.0
Workload Analysis					
May - August	2.271*** (0.762)	3.080*** (0.742)	3.868*** (0.656)	4.696*** (0.608)	70.0
Other months	2.228* (0.143)	3.110*** (0.786)	3.854*** (0.595)	4.648*** (0.752)	35,5

Note: Standard errors in parentheses; '***', '**', and '*' represent significance at 0.01, 0.05, and 0.1 levels, respectively. $\hat{C}_k$, k=1, 2, 3, and 4 is an estimated cutoff point for each yield grade and is defined in the equation (9).

3.6.5 The Results of Hypothesis Test Using the Bootstrap Approach

We employed a bootstrap approach testing whether the differences among estimated grade thresholds were statistically significant. The bootstrapping approach provides a method to verify the robustness of the non-parametric results shown above. The bootstrap approach introduced by Efron (1979) is used to produce accurate inferences such as confidence intervals without any assumptions about data distributions. It first generates bootstrap samples from the original data using a random sampling method. Based on these samples, it estimates standard errors and confidence intervals of point estimates. The bootstrap approach also provides the distributions of point estimates from the bootstrap samples which can be used to test statistical hypotheses around the estimator. We generated one thousand bootstrap samples from our original dataset using the resampling method[11] and obtained the distributions of estimated thresholds from the samples. Using these distributions, we were able to test the difference between or among estimated thresholds across time for each analysis in this article.

Table A.1 presents the bootstrapping results. Differences among estimated thresholds over time are statistically significant. As shown in Table A.3. 5, the estimated threshold between grades 1 and 2 over weekdays (2.2) is statistically different from the one for weekends (2.4). Table A.1 also shows that the thresholds before (2.3) and during (2.0) the financial crisis are statistically different from each other. The average estimated cutoff points obtained from the bootstrap method are similar to those obtained from the

[11] The method of random sampling selects units for bootstrap samples with equal probability. Also, a unit can be selected for the sample more than one.

non-parametric estimation supporting the robustness of the non-parametric estimation results.

The difference in sample sizes across time (seasons, weekdays and weekends) could influence the estimation. As shown in the previous simulation and bootstrap analysis, however, the non-parametric model in this study provides consistent and efficient estimates with different sample sizes.

3.7 Conclusions

In this article, a non-parametric approach was adopted to enhance the consistency of the cutoff point estimation model. Given the fact that the conditional distributions of yield grades 1 and 5 indeed follow non-normal distributions, this non-parametric model has the advantage that the assumption of the normal distribution is relaxed so that we could estimate cutoff points more consistently. The results of our simulation studies supported the suitability of the non-parametric model. The model was applicable to simultaneous estimation of multiple cutoff points without the normal distribution assumption in further research.

The unique data and methodology were employed to investigate the existence and potential sources of grading bias. We found the existence of systematical grading bias in the beef industry and the potential sources of grading bias, such as graders' perception bias and economics events influencing producers' and packers' return. These results show the possibility that grading bias was attributable to psychic causes, such as the nature of human beings.

4. EFFECTS OF WEATHER STRESS ON FEEDLOT CATTLE PERFORMANCE

4.1 Introduction

The thermoneutral zone of health beef cattle is between 32° and 77°F. Thermal stress outside this range leads to reductions in performance and reproductive efficiency and increases in morbidity and mortality rates of cattle. These adverse influences result in beef cattle producer losses. According to USDA reports (2006, 2011, 2017), estimated death losses of cattle and calves due to a severe weather conditions in 2015 totaled $382 million, which amounted to 122.1% and 39.4% increases relative to the total losses experienced in 2005 ($172 million) and 2010 ($274 million), respectively. Further, climate scientists predicted that climate risk would increase in the future (IPCC 2013). The projected climate risk increase coupled with the observed surge in death losses caused by adverse climate conditions suggests that climate-related risk management may become more crucial in beef production.

In terms of the climate risk, IPCC scientists project that global air temperature will increase, and severe weather events will occur more often (IPCC 2012; IPCC 2013). This research examines the influence of climate conditions on beef carcass traits, such as the yield index, marbling score, ribeye area, and fat thickness. Furthermore, estimations will be made on the changes in insurance premium rates that are needed to mitigate potential losses from increases in extreme weather. Finally, this study also examines how the variation of corn prices, and transportation stress influenced beef cattle production.

4.1.1 Literature Background

A voluminous literature has investigated how heat or cold stress influences cattle behavior and performance as well as its negative effects on death loss, health and reproductive traits. Studies have found that heat-stressed beef cattle reduce dry matter intake and increase water intake to decrease metabolic heat generation and keep steady body temperature (Hahn 1985; Collier, Dahl, and Van Baale 2006; Bernabucci *et al.* 2009; O'Brien *et al.* 2010). Cold stress also has been found to have an effect with findings of decreasing weight gain and feed-to-gain ratios during the winter in the Midwest and Southern California of the USA (Elam 1970, Birkelo 1991), as well as in some areas of Canada (Webster, Chlumechy, and Young 1970; Hidiroglou and Lessard 1971; Milligan and Chrisfision 1974). Several event studies and articles also documented the impact of climate disasters on producer losses. Beef cattle producers suffered losses following extreme heat waves in 1995 and 1999 (Hahn *et al.* 2001), severe winter storms in 1996 and 1997 (Mader 2003), and exceptional drought in the Southern High Plains during 2010 (Strom 2013).

In the same vein, animal scientists have examined the relation of weather stress to the yield index and marbling score, which represent meat productivity and quality, respectively. In relation to cold stress, Piao and Baik (2015) showed that yield index was worsened by severe winter weather conditions, while marbling score was not influenced. On the other hand, Mader, Dahlquist, and Gaughan (1997) and Mader (2003) found that marbling score and fat thickness were improved or unchanged under mild cold stress.

Their result suggests that marbling in ribeye muscle could increase when beef cattle are better adapted to cold stress.

When it comes to heat stress, Mitlöhner et al. (2001) found no significant differences in marbling scores, yield grades, and quality grades between shaded and unshaded beef cattle. Clarke and Kelly (1996) found that the provision of shade in summer to reduce heat stress provided no significant increase in marbling score. Mader and Davis (2004) found that marbling score increased when water sprinkler-based cooling was provided in summer. Given these conflicting heat stress related findings, this research will address how heat and cold stress separately affect yield index and marbling score.

Previous literature (Piao and Baik 2015; Gaughan *et al.* 2008; Hahn, Mader, and Eigenberg 2003; Mader 2003; Ames and Insley 1975) have used a Temperature-Humidity Index (THI) and a Wind-Chill index (WCI) developed by Thom (1959) and Siple and Passel (1945) respectively to measure weather stress in livestock production. However, these indices were originally developed to measure humans' discomfort related to weather condition (Tew, Battel, and Nelson 2002). This study used the Comprehensive Climate Index (CCI) which recently developed by Mader, Johnson, and Gaughan (2010) to estimate heat and cold stress in the feedlot. The CCI is computed using humidity, ambient temperature, solar radiation, and wind speed. Mader, Johnson, and Gaughan (2010) also suggested thresholds to convert index values into the level of animal stress in fed cattle. We used this recently introduced index to measure weather-related beef cattle stress in order to estimate the impact of climate stress on beef cattle production.

Although there is a voluminous literature examining the impact of weather stress on beef cattle production, very few studies have attempted to estimate producer losses or addressed ways to manage climate-related risks. Belasco, Cheng, and Schroeder (2015) investigated the effect of weather stress on feedlot performance measures, such as average daily gain, feed conversion, and mortality rate. They also derived fair insurance premium rates for a livestock insurance product that would be needed to mitigate potential losses from extreme weather. They suggested that an important dimension of producers' expected losses of beef cattle from weather stress and needed insurance premium rates increases can be calculated using USDA yield and quality grades because those grades mostly determine the market value of a beef cattle. Following their suggestion, this study will estimate the expected losses or needed insurance premium rate increases using data on USDA quality (marbling score) and yield (yield index) grades that were collected from a Midwest packing plant for the period May 2005 – October 2008. In this study, the estimated expected losses and insurance premium rates were estimated based on producer losses from decreased market values of survived beef cattle from weather stress. The increased climate management cost in feedlots and feed and beef prices shift due to climate stress were not included in the expected losses.

In addition to climate stress, corn prices are the primary determinant of beef producers' return (McDonald and Schroeder 2003). Moreover, the variation of corn prices indicates a change in a grain cost of beef cattle production, because the percentage of corn in the feed grain consumed by livestock is over 80 percent (Anderson and Trapp 2000). While many past studies have focused on the relation of corn prices to weight gains and producer profitability (Langemeier, Schroeder, and Minter 1992; Mark, Schroeder, and Jones 2000; McDonald and Schroeder 2003; Kaknaroglu et al. 2005; Tatum 2012), there has not been much analysis on the influence of corn prices on marbling score and yield index which in turn determine a cattle price. Furthermore, corn prices surged due to the corn ethanol production increase that was stimulated by Energy Policy Acts in 2005 and 2007, as shown in Figure A.7. Corn prices increased 116.3% as the use of corn for ethanol production rose 174.1% during the sample period of this research (May 2005 - September 2008). This study, thus, investigated the relation of corn prices on beef cattle performance to reveal how the surge in corn-based ethanol production influenced beef cattle carcass grades.

Transport stress is another significant stressor which deteriorates beef cattle performance. Injuries and carcass bruising have been observed after transportation. Numerous studies (Tarrant et al. 1992; Eldridge and Winfield 1988; Coffey et al., 2001; Cernicchiaro et al. 2012) provided evidence of a decrease in carcass weight and a high risk of injury during transportation. Recent studies also found that transportation diminished animal’s welfare (Mitchell and Kettlewell 2008; Goldhawk et al. 2014). Despite these interesting studies, a little research has attempted to identify the impact of transport stress on beef cattle attributes, including yield index and marbling score. This research, thus, investigated the effect of travel time from feedlot to a packing plant on the yield index, marbling score, ribeye area, and fat thickness. Instead of distance, the travel time (total minutes) was used as a proxy for transport stress, because, with respect to livestock welfare, a total duration is more important than a total distance (Schwartzkopf-Genswein 2016).

4.2 Data

As shown in Table 4.1, beef cattle carcass grading data on marbling score, yield index, fat thickness, and ribeye area were obtained from a Nebraska packing plant for the period of May 2005 through October 2008. Historical and geographical climate data were obtained from the National Renewable Energy Laboratory. The data contains hourly relative humidity, ambient temperature, solar radiation, and wind speed for each location of feedlots. The climate and packing plant data were combined using the location information of each feedlot and the processed date of an individual carcass. In addition, historical corn prices were collected from USDA ERS to be merged with the climate and packing plant data based on the processed date of each carcass. The transport times from feedlots to the packing plants were estimated using Google maps and combined with other data.

Table 4.1. Summary Statistics (Num. of Obs. = 16,949), May 2005- October 2008

	Mean	Std. Dev.	Min	Max
Yield Index	3.18	0.74	0.26	6.35
Marbling Score	5.06	1.02	1.50	10.60
Fat opposite REA (Inches)	0.52	0.17	0.02	1.40
Rib Eye Area (Inches^2)	12.44	1.62	0.00	22.40
Hours_Heat Stress*	490.51	566.10	4.00	2,395.00
Hours_Cold Stress*	2,170.16	837.42	19.00	3,377.00
Corn Price ($/bushel, 6M Average)	2.92	0.96	1.91	5.23
Fertilizer Price ($/ton, 6M Average)	83.70	42.64	56.79	245.20
Minutes to Packing Plant	232.53	74.06	40.00	584.00
Dummies				
Carcass Weight (1 if carcass weight < 800 lbs.)	0.61	0.49	0	1
Summer (June- August)	0.44	0.50	0	1
Fall (September - November)	0.08	0.28	0	1
Winter (December – February)	0.04	0.19	0	1
2006	0.36	0.48	0	1
2007	0.34	0.47	0	1
2008	0.17	0.38	0	1
Financial Crisis (1 if processed date > July 2007)	0.21	0.41	0	1

Source: The yield index, marbling score, fat opposite REA, and rib eye area data were collected from a large-scale Midwest packing plant from May 2005 to October 2008; The weather data (relative humidity, ambient temperature, solar radiation, and wind speed) for computing hours exposed to heat and cold stress data were collected from National Renewable Energy Laboratory; Corn and fertilizer prices were collected from USDA ERS; Minutes to packing plant data were collected from Google maps.
* Hours exceeding weather thresholds (heat stress: CCI > 25; cold stress: CCI < 0).

Mature feeder cattle are moved to feedlots and spend the next four to six months under feed. In feedlots, they feed a diet consisted of grain, forage, and renewable feed sources. Most beef cattle are processed when they reach market weight (1,200 to 1,400 pounds). Given the beef cattle life-cycle, four or six months in feedlots before cattle are processed are a critical period of determining meat productivity and quality. Thus, six-month averages of corn prices before the processed date of the individual carcass were computed and were used as variables to identify how the variations of these prices influenced the quality and yield of beef cattle. Further, six-month total hours of heat and cold stress exposure calculated using CCI before cattle are processed were used as proxies of weather stresses.

4.2.1 Marbling Score and Yield Index

The degree of marbling score and physiological maturity determine the USDA quality grade. Given the fact that 97% of beef cattle are processed before 30 months (Garcia *et al.* 2008), it is reasonable to assume that the main factor determining the quality grade is the marbling score. The USDA quality grade represents palatability of meat and is segregated into six grades (Prime, Choice, Select, Standard, Commercial, and Utility). The higher marbling score, the better the USDA quality grade that is assigned. When the marbling score is higher than 8.0, the beef carcass is graded at the highest level- Prime. The marbling scores used were assigned by camera-based grading systems.

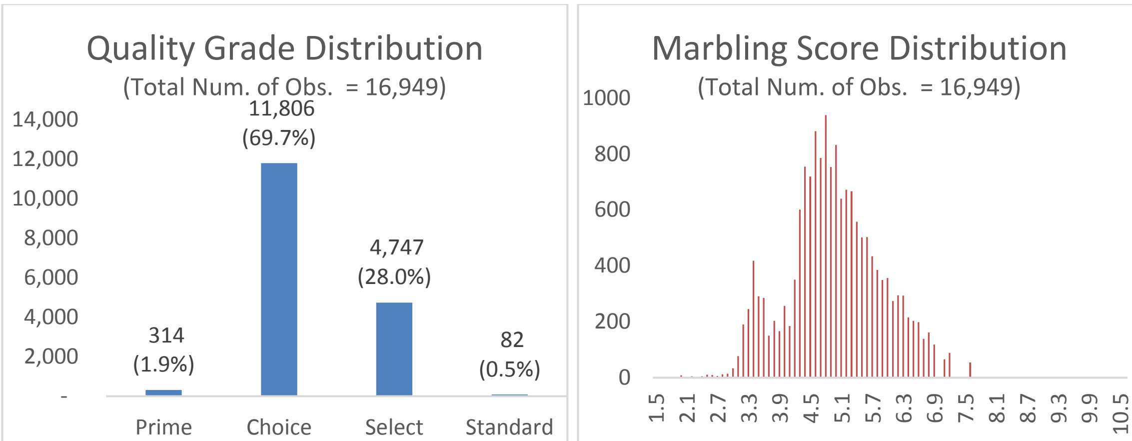
The yield index represents the amount of edible meat from beef cattle. The index is calculated based on the following formula:

(10) Yield index = 2.5 + 2.5 fat thickness + 0.2 kph + 0.0038 hot carcass weight – 0.32 rib-eye area.

As shown in the equation (10), the primary determinants of yield index (grade) are fat thickness and ribeye area. As external fat over the outside of the 12th ribeye becomes thinner and ribeye area at the 12th rib gets wider, the yield index of a carcass becomes smaller (better). The USDA yield grade made up of five grades: yield grade 1 (best) through 5 (worst). As the yield index becomes smaller, the USDA yield grade increases. In the cattle auction market, the value of beef cattle is mostly determined by USDA quality and the yield grade. In this study, the yield index and marbling score were used as proxies for meat quantity and quality. Along with the yield index and marbling score, fat thickness and ribeye area were also used to represent beef carcass quality.

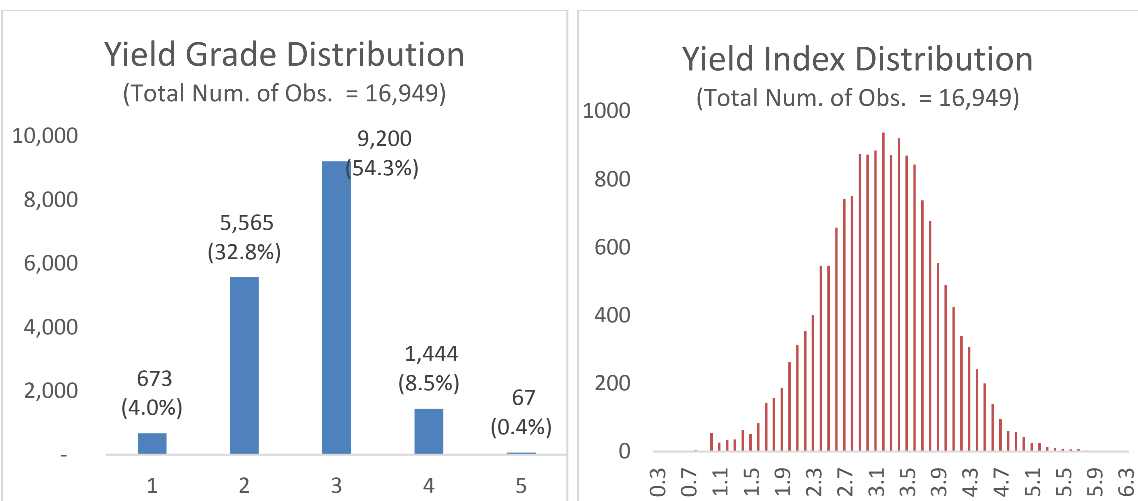
Figure 4.1 illustrates that most of the beef carcasses in this study were graded as Choice (69.7%) or Select (28.0%), and Yield Grade 2 (32.8%), or Yield Grade 3 (54.3%). These data are not very different from national statistics (Table 4.2) implying that the data likely permits national inferences.

Panel A. Distributions of Quality Grade and Marbling Score



Source: The quality grade, marbling score data were collected from a large-scale Midwest packing plant from May 2005 to October 2008.

Panel B. Distributions of Yield Grade and Yield Index



Source: The yield grade, yield index data were collected from a large-scale Midwest packing plant from May 2005 to October 2008.

Figure 4.1. Distributions of Quality Grade, Marbling Score, Yield Grade, and Yield Index.

Table 4.2. National Summary of Meat Graded (million pounds, percentage of total graded in parentheses)

	2005		2006		2007		2008	
Quality Grade								
Prime	602	(3.1)	577	(2.9)	525	(2.6)	595	(2.9)
Choice	11,133	(57.3)	11,367	(56.2)	11,655	(58.0)	12,459	(61.0)
Select	7,679	(39.5)	8,279	(40.9)	7,872	(39.1)	7,312	(35.8)
Standard	29	(0.1)	6	(0.0)	56	(0.3)	70	(0.3)
Total	19,443	(100.0)	20,229	(100.0)	20,108	(100.0)	20,436	(100.0)
Yield Grade								
YG1	2,046	(10.6)	1,800	(8.9)	1,758	(8.8)	1,634	(9.2)
YG2	7,843	(40.5)	7,525	(37.3)	7,373	(36.9)	6,688	(37.6)
YG3	7,735	(39.9)	8,488	(42.1)	8,679	(43.4)	7,575	(42.6)
YG4	1,556	(8.0)	2,040	(10.1)	1,909	(9.5)	1,643	(9.2)
YG5	199	(1.0)	314	(1.6)	280	(1.4)	246	(1.4)
Total	19,379	(100.0)	20,167	(100.0)	19,999	(100.0)	17,786	(100.0)

Source: The USDA AMS

4.2.2 Comprehensive Climate Index

Comprehensive Climate Index (CCI) suggested by Mader, Johnson, and Gaughan (2010) was used to account for weather-related stress in beef cattle. The index is calculated using relative humidity (RH), ambient temperature (AT), solar radiation (SR), and wind speed (WS) as follows:

(11) $CCI = AT + RH^c + WS^c + SR^c$,

where RH^c, WS^c, and SR^c are correction factors to relative humidity (RH), solar radiation (SR), and wind speed (WS), respectively. The correction factors are

(12) $\mathrm{RH^c} = \mathrm{e}^{0.00182\times\mathrm{RH}+(1.8\times10^{-5})} \times [0.000054 \times \mathrm{AT}^2 + 0.00192 \times \mathrm{AT} - 0.0246] \times [\mathrm{RH} - 30]$,

(13) $\mathrm{WS^c} = \left[\frac{-6.56}{e^{\left\{\left[\frac{1}{(2.26\times WS+0.23)^{0.45}}\right]\times[2.9+1.14\times10^{-6}\times WS^{2.5}-log_{0.3}(2.26\times WS+0.33)^2\right\}}}\right] - 0.00566 \times WS^2 + 3.33$,

(14) $SR^c = 0.0076 \times SR - 0.00002 \times SR \times AT + 0.00005 \times AT^2 \times \sqrt{SR} + 0.1 \times AT - 2$,

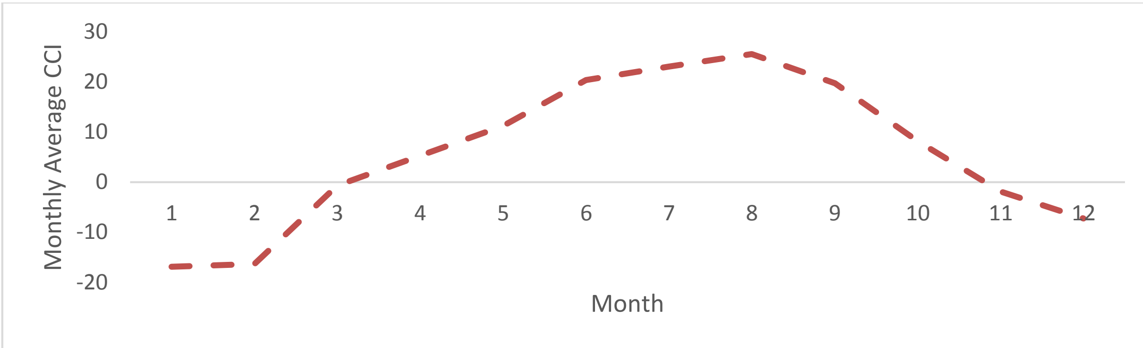
where AT, WS, and SR are measured in Celsius, meters/second, and watts/meter, respectively. The correction factors represent the effect of weather variables on animal well-being and comfort. When the index is above (below) 25 (0) in Table 4.3, then animals are exposed to cold (heat) stress.

Table 4.3. The degree of weather stress

CCI range	Amount of heat tress	CCI range	Amount of cold stress
CCI < 25	None	CCI > 0	None
CCI ≥ 25	Range where stress occurs	CCI ≤ 0	Range where stress occurs
25 < CCI ≤ 30	Mild	0 < CCI ≤ -10	Mild
30 < CCI ≤ 35	Moderate	-10 < CCI ≤ -20	Moderate
CCI > 35	Severe	CCI < -20	Severe

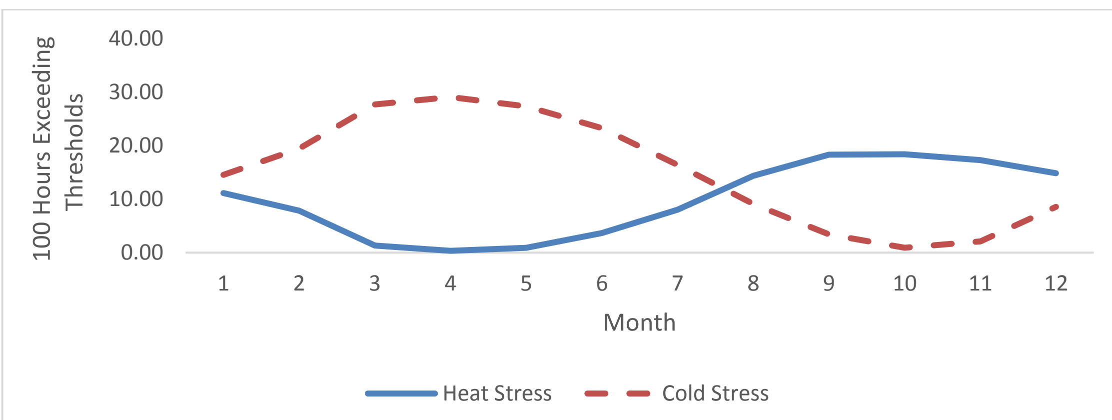
Source: Mader, Johnson, and Gaughan (2010)
Note: CCI stands for Comprehensive Climate Index suggested by Mader, Johnson, and Gaughan (2010)

Figure 4.2 illustrates that monthly average comprehensive climate index increased in spring and summer and declined in fall and winter. Figure 4.3 shows average values in the 6 months preceding slaughter. The figure shows beef cattle slaughtered between March and May were mostly exposed to cold stress, while beef cattle slaughtered between September and November were mostly exposed to heat stress. The different weather stress exposure pattern across seasons supports the idea of separately analyzing the impacts of cold and heat stress on feedlot performance. Approximately 88.0% (14,923 heads of 16,932) of beef cattle in our data were slaughtered in spring (March to May) and summer (June to August) at the peak of beef consumption. This indicates that beef cattle were exposed to more cold stress than heat stress.



Source: The weather data (relative humidity, ambient temperature, solar radiation, and wind speed) for computing hours exposed to heat and cold stress data were collected from National Renewable Energy Laboratory.
Note: CCI stands for Comprehensive Climate Index suggested by Mader, Johnson, and Gaughan (2010); the data are the monthly average CCI of 32 cities in where 36 producers in the dataset are located.

Figure 4.2. Monthly Average Comprehensive Climate Index, May 2005- October 2008.



Source: The weather data (relative humidity, ambient temperature, solar radiation, and wind speed) for computing hours exposed to heat and cold stress data were collected from National Renewable Energy Laboratory.
Note: CCI stands for Comprehensive Climate Index suggested by Mader, Johnson, and Gaughan (2010); the data are the monthly average CCI of 32 cities in where 36 producers in the dataset are located.

Figure 4.3. Averaged Hours Exceeding Weather Stress Thresholds (Heat: CCI>25, Cold: CCI<0) for 6 Months (180 days) before Processed by Month

4.3 Methodology

A random effects regression model, also called a hierarchical linear model, was used to estimate the impact of cold and heat stress on beef cattle production outcomes. The model is useful for controlling for an unobserved group effect within an individual-specific effect. The data for this research does not include specific producer-level feedlot information such as feeding styles, environment-stress management methods, calf condition and stress exposure prior to the feedlot, and types of beef cattle. Beef cattle outcomes, however, are influenced by feedlot management which is heterogeneous across feedlots. Therefore, it was necessary to control for unobserved producer-level-effects through a random effects regression model.

Consider the following for carcass *i(j)* (i(j) = 1, 2, …, n_j for producer *j*) within producer *j* (*j* = 1, …, *J* producers in the sample),

$$
\begin{aligned}
(15)\quad Y_{ij} = {} & \beta_0 + \beta_1\, Hours\_Heat\ Stress_{ij} + \beta_2\, Hours\_Cold\ Stress_{ij} + \beta_3\, Pofcorn_{ij} \\
& + \beta_4\, Minutes\ to\ Plant_{ij} + Carcass\ Weight\ Dummy + Annual\ Dummies \\
& + Seasonal\ Dummies + Financial\ crisis\ Dummy + u_j + e_{ij},
\end{aligned}
$$

where Y_{ij} = [*Yield Index*$_{ij}$, *Marbling Score*$_{ij}$, *Ribeye Size*$_{ij}$, *Fat Inches*$_{ij}$,] for carcass *i(j)* from producer *j*; $Hours\_\ Heat\ Stress_{ij}$ $(Hours\_\ Cold\ Stress_{ij})$ is the total hours in which CCI exceeds the thresholds of heat (cold) stress in the six previous months; $PofCorn_{ij}$, $PofFertilizer_{ij}$ are the six-month average prices of corn, and fertilizer before beef cattle were processed in a packing plant; estimates β_k k= {0, 1, 2, 3, 4} are each 4×1 vectors; u_j

represents an unobserved effect caused by producer *j* and is considered a random parameter that follows a normal distribution with mean 0 and variance σ^2_u, $N(0, \sigma^2_u)$; e_{ij} is an independent residual distributed normally, $N(0, \sigma^2_e)$, in the population of carcasses.

The method of instrumental variable analysis was adopted to control for unmeasured confounding effects between corn prices and beef cattle performance traits. Based on our search, there is no study that has identified corn prices as an endogenous regressor when estimating the effects of corn prices on cattle production. However, there are a number of findings in the literature regarding the relation between corn prices and cattle prices (Schuring, Huffman, and Fan 2011; Zhao, Xiaodong, and Hennessy 2009; Anderson and Trapp 2000; Albright, Schroeder; Langemeier 1994; Arzac and Wilkinson 1979; Marsh 2007; Tejeda and Goodwin 2011). These studies have provided empirical evidence that corn prices affected the price and supply of beef cattle and thus suggest that there is a chance that corn prices and cattle performance could jointly influence each other. Therefore, six-month averages of fertilizer prices were used as an instrument in estimating corn prices to resolve endogeneity issues in the model. The fertilizer price is one of the primary determinants of the corn price but is not related to cattle production. The Hausman test for the instrumental variable indicated that a corn price is an endogenous variable in the model. In addition, we included the squares of hours exposed to heat/cold stress and minutes to packing plant to estimate the nonlinear relations of those variables with beef carcass traits. We, however, found that hours exposed to heat/cold stress are strong correlated with their squares during our sample period.

Coefficients of those squares, thus, were separately estimated to avoid a multicollinearity issue.

Prior literature showed that placement season and entry weight affect the performance of beef cattle (Belasco, Ghosh, and Goodwin 2009; Lawrence, Wang, and Loy 1999; Schroeder et al. 1993). The available beef grading data did not contain information on entry weight and placement date of beef cattle. Thus, seasonal and carcass weight dummies were contained in the regression model to control the effects of placement time and entry weight. The impact of the general economic situation was also controlled by adding dummies for the 2008-2009 financial crisis. Moreover, hours, instead of days, were used as the unit of the weather stress index to precisely measure the intensity of climate stress.

4.4 Effect of Weather Stress on Beef Cattle Production

As shown in Table 4.4, the beef carcass yield index increased (worsened) with longer exposure to heat or cold stress. This is consistent with the previous finding that cattle who had experienced severe winter weather condition had a worse yield grading index as found by Piao and Pack (2015) who suggested that heat and cold stress worsened carcass yield as a result of the decline of stress reduced feed intake and body weight. Moreover, the estimated coefficient of heat stress (0.00023) is larger than the one for cold stress (0.00015) suggesting that it may be more critical to manage heat stress in improving carcass value.

Regarding marbling score, there were conflicting estimation results associated with heat and cold stress. While cold stress worsened marbling score, heat stress improved it. Unlike yield index, there is no clear theoretical and empirical explanation about how heat and cold stress influence marbling score. Anderson and Trapp (2000) indicated that finishing fed cattle with corn is essential to reach Choice grade. This statement implies that marbling score could be mainly affected by corn intake in feedlots. One possible explanation for the relationship between marbling score and heat stress, thus, is that producers could provide high-quality feed to mitigate heat stress when the stress was heightened. This better-quality feed could result in the improvement of marbling scores when heat stress escalated. Past empirical studies also have provided conflicting results. Clarks and Kelly (1996) and Mitlöhner et al., (2001) found that the provision of shade or sprinklers did not affect marbling score, whereas, Mader and Davis (2004) provided empirical evidence that marbling scores of cattle that were provided with water on pen surfaces in the afternoon were higher than those provided with water in the morning.

A rise in corn prices during the sample period worsened marbling score as shown in Table 4.4. Lardy and Larson (2006) found that marbling scores of beef cattle fed low-density corn were lower than those fed high or medium density corn. Increased corn prices could influence meat quality if feedlot operators substituted high or medium density corn with low-density corn. Unlike marbling score, yield index was improved while corn prices rose. Anderson and Trapp (2000) revealed that as the corn-steer price ratio raised, the entry weight of feedlots and out-weight of live cattle increased.

Producers would choose heavier or older feeders with high corn prices because of increased feeding costs. Their preference on high-performance feeders with high corn prices would result in the improvement of yield index.

This study also found that as transport stress increased, ribeye area shrank, and yield index worsened. This result supports prior studies documenting beef cattle lost weight during transportation. Tarrant et al. (1992) documented that weight loss from a 24 hours trip averaged 8.3%. Ribeye area is a primary determinant of yield grade directly influencing the monetary value of beef carcass in the grid pricing. Therefore, managing livestock's transport stress can result in economic advantages. This result shows that producers' efforts to mitigate transport stress, e.g., managing, transport duration, trailer design, ventilation, and loading density can be compensated. In addition, the negative coefficient of a squared transport stress variable in Table 4.4 (column 3) indicates that the increasing rate of transport stress effect on yield index decreased as a trip time to a packing plant increased. This finding implies that beef cattle adapted to the environment of the transport truck, as they spent more time in the truck.

Table 4.4. The Estimation Results of the Random Effect Model

	Yield Index (Best is 1 worst is 5)			Marbling Score (Best is high number worst is low)		
	(1)	(2)	(3)	(4)	(5)	(6)
Hours_Heat Stress	0.023*** (0.000)		0.025*** (0.000)	0.026*** (0.002)		0.028*** (0.001)
Hours_Cold Stress	0.015*** (0.001)		0.016*** (0.001)	-0.018*** (0.002)		-0.017** (0.005)
Hours_Heat $Stress^2$		0.001*** (0.002)			0.002*** (0.000)	
Hours_Cold $Stress^2$		0.000** (0.012)			-0.000*** (0.000)	
Minutes to Packing Plant	0.089*** (0.081)	0.089* (0.095)	0.469** (0.010)	0.053 (0.306)	0.032 (0.540)	0.339 (0.070)
Minutes to Packing $Plant^2$			-0.066** (0.028)			-0.051 (0.105)
Corn Price_6M Avg	-0.352*** (0.000)	-0.380*** (0.000)		-0.909*** (0.000)	-0.880*** (0.000)	-0.901*** (0.000)
Dummies						
Carcass Weight	-0.130*** (0.000)	-0.129*** (0.000)	-0.131*** (0.000)	0.071*** (0.000)	0.073*** (0.000)	0.071*** (0.000)
Summer	-0.114*** (0.000)	-0.085*** (0.000)	-0.114*** (0.000)	0.066*** (0.005)	0.120*** (0.000)	0.066** (0.005)
Fall	-0.146*** (0.002)	-0.189*** (0.000)	-0.145** (0.002)	-0.007*** (0.916)	0.066 (0.274)	-0.005 (0.941)
Winter	-0.240*** (0.000)	-0.210*** (0.000)	-0.238*** (0.000)	-0.325*** (0.000)	-0.231*** (0.000)	-0.324*** (0.000)
2006	0.311*** (0.000)	0.309*** (0.000)	0.310*** (0.000)	0.604*** (0.000)	0.607*** (0.000)	0.603*** (0.000)
2007	0.551*** (0.000)	0.600*** (0.000)	0.541*** (0.000)	2.217*** (0.000)	2.187*** (0.000)	2.205*** (0.000)
2008	0.542*** (0.000)	0.635*** (0.000)	0.528*** (0.000)	3.957*** (0.000)	3.959*** (0.000)	3.941*** (0.000)
Financial Crisis	0.193*** (0.000)	0.185*** (0.000)	0.189*** (0.000)	-0.148*** (0.002)	-0.220*** (0.000)	-0.154** (0.001)
σ_u	0.292	0.309	0.322	0.298	0.285	0.319
σ_e	0.683	0.678	0.678	0.682	0.887	0.886
ρ	0.155	0.172	0.184	0.160	0.094	0.114
Within R^2	0.047	0.061	0.061	0.048	0.125	0.126
Between R^2	0.075	0.431	0.488	0.069	0.642	0.682
Overall R^2	0.402	0.090	0.077	0.349	0.202	0.203

Note: P values in parentheses; '***', '**', and '*' represent significance at 0.01, 0.05, and 0.1 levels, respectively. Hours_Heat Stress, Hours_Cold Stress, and Minutes to Packing Plant were divided by 100 to adjust the units of corresponding coefficients. Red values mean quality worsens, blue improves.

Table 4.4. Continued

	Ribeye Size			Fat Inches		
	(7)	(8)	(9)	(10)	(11)	(12)
Hours_Heat Stress	-0.042** (0.001)		-0.045*** (0.001)	0.002 (0.172)		0.002 (0.164)
Hours_Cold Stress	-0.018* (0.057)		-0.020** (0.037)	0.003** (0.006)		0.003** (0.006)
Hours_Heat Stress^2		-0.001 (0.133)			0.000 (0.444)	
Hours_Cold Stress^2		0.000 (0.391)			0.000*** (0.000)	
Minutes to Packing Plant	-0.210** (0.025)	-0.226** (0.017)	-1.055** (0.001)	0.017* (0.098)	0.017 (0.130)	0.060* (0.095)
Minutes to Packing Plant^2			0.148** (0.006)			-0.008 (0.210)
Corn Price_6M Avg	0.540*** (0.000)	0.613*** (0.000)	0.524*** (0.000)	-0.036*** (0.001)	-0.041*** (0.000)	-0.038*** (0.000)
Dummies						
Carcass Weight	-1.215*** (0.000)	-1.216*** (0.000)	-1.214*** (0.000)	-0.019*** (0.000)	-0.019*** (0.000)	-0.019*** (0.000)
Summer	0.211*** (0.000)	0.200*** (0.000)	0.211*** (0.000)	-0.023*** (0.000)	-0.017*** (0.000)	-0.022*** (0.000)
Fall	0.430*** (0.000)	0.436*** (0.000)	0.426*** (0.000)	-0.007 (0.517)	-0.014 (0.205)	-0.005 (0.632)
Winter	0.752*** (0.000)	0.745*** (0.000)	0.748*** (0.000)	-0.004 (0.712)	0.002 (0.879)	-0.004 (0.719)
2006	-0.746*** (0.000)	-0.735*** (0.000)	-0.745*** (0.000)	0.015** (0.002)	0.016** (0.002)	0.016** (0.002)
2007	-1.138*** (0.000)	-1.251*** (0.000)	-1.115*** (0.000)	0.018 (0.247)	0.026* (0.071)	0.021 (0.176)
2008	-1.025*** (0.000)	-1.203*** (0.000)	-0.991*** (0.000)	-0.015 (0.617)	-0.001 (0.984)	-0.010 (0.753)
Financial Crisis	-0.093 (0.197)	-0.131* (0.087)	-0.083 (0.251)	0.055*** (0.000)	0.055*** (0.000)	0.055*** (0.000)
σ_u	0.303	0.537	0.559	0.364	0.064	0.062
σ_e	0.682	1.348	1.347	0.680	0.158	0.158
ρ	0.165	0.137	0.147	0.223	0.140	0.135
Within R^2	0.048	0.195	0.196	0.053	0.029	0.029
Between R^2	0.070	0.644	0.680	0.087	0.324	0.339
Overall R^2	0.361	0.248	0.230	0.457	0.044	0.040

Note: P values in parentheses; '***', '**', and '*' represent significance at 0.01, 0.05, and 0.1 levels, respectively. Hours_Heat Stress, Hours_Cold Stress, and Minutes to Packing Plant were divided by 100 to adjust the units of corresponding coefficients.

4.5 Simulated Producers' Losses and Insurance Premium Rates

The effect of heat and cold stress on producer losses was simulated using estimated coefficients of yield index and marbling score that indicate the effect of an hour-long increase in weather stress on the magnitude of the index and score. Historical premiums and discounts of USDA grades for each grade were used to transform yield index and marbling score into a monetary term. Furthermore, premium rates for a weather-indexed livestock insurance product were computed using the simulated losses and the probability of hours exposed to weather stress.

4.5.1 Simulated Losses

As documented in the previous and current literature, escalated heat and cold stress had a significant effect on beef cattle production. This research also found that heat and cold stress have a different effect on marbling score. While heat stress improved marbling score, cold stress exacerbated it. Due to the different effect of each stressor, heat and cold stress were analyzed separately in this section.

Initial values of marbling score (4.5), and yield index (3.5) were assumed as a base from which to simulate producer losses from heat and cold stress. In turn changes in yield index and marbling score were simulated by evaluating out an equation under increased hours exposed to heat and cold stress. The simulated yield indexes and marbling scores across hours resulted in altered USDA yield and quality grades. The simulated losses, as shown in Figure A.8, were computed across a range of weather-stress exposure hours using the average discounts and premiums for each grade in Table

4.5. Finally, the averages of discounts and premiums for each quality and yield grade were calculated using the historical USDA premiums and discounts during the sample period.

As shown in Figure A.8 (Panel A), the positive impact of heat stress on quality grade was not significant. Although simulated losses related to heat stress decreased at some range of hours, they did not turn into profits. Regarding cold stress, losses steadily increased as weather stress increased as illustrated in Figure A.8 (Panel B). This also indicates that discounts from worsened marbling scores were higher than those from exacerbated yield indexes.

Table 4.5. Average Premiums and Discounts for Each Quality and Yield Grade, May 2005- October 2008

Quality Grade	Average Premiums/Discounts ($)	Yield grade	Average Premiums/Discounts ($)
Prime (8.0)	15.43	YG1 (1.99)	4.13
CAB (7.0-7.9)	1.61	YG2 (2.0-2.99)	2.00
Choice (5.0-6.9)	0	YG3 (3.0-3.99)	-0.30
Select (4.0-4.9)	-9.78	YG4 (4.0-4.99)	-15.22
Standard (3.9)	-15.79	YG5 (5)	-22.59

Source: USDA ERS National Weekly Direct Slaughter Cattle – Premiums and Discounts Report.

4.5.2 Insurance Premium Rates

Insurers have developed products that mitigate risks in beef cattle production, such as livestock mortality losses, declines in livestock prices, and the loss of gross margin. However, they have not introduced weather-index insurance products covering losses from reductions in carcass value caused by weather stress. It is necessary to compute premiums rates to provide a basis for designing the products. This study, thus, calculated insurance premium rates based on the probability of hours exposed to weather stress and simulated losses for each hour as follows:

$$(16)\quad Expected[loss|hours > S] = \sum_{h=1}^{H} Prbability[hours = S + h] \times Simulated[loss|hours = S + h],$$

where h is the number of hours over S (Strike exposure hour level), and H is maximum hours. The probability of hours exceeding the strike level was computed using weather data collected from the eastern Nebraska location from 1998 to 2015 as described in Figure 4.6. The compensation is determined by hours that the CCI threshold surpasses the strike. With this type of insurance, expected losses are actuarially fair premium rates for an event. Results in Table A.2 show that individual premiums for various cold stress strike levels at 2,000, 2,200 and 2,500 hours are \$2.60, \$1.98, and \$1.11, respectively. The premium rates increase with the probability of receiving insurance benefits.

4.6 Conclusions

This research attempted to provide empirical evidences how climate stress influenced beef cattle production: yield index, marbling score, ribeye size, and fat thickness. We, first, found that cold and heat stress led to an increased, less valuable yield index. Meanwhile, marbling score was only worsened by cold stress, but it was improved by heat stress. According to the simulation analysis, furthermore, weather stress steadily increased producer losses, as the effect of improved marbling score attributed to heat stress had a limited impact on profitability relative to changes in the yield index. These findings suggest that climate risk management in beef cattle production would be a valuable way of avoiding heat stress caused producer losses due to warmer future conditions. There are a number of suggested adaptation strategies such as land use management, genetic changes, feeding style transformations, and modifications in species. (Zhang, McCarl, and Jones, 2017). These strategies would be effective to limit the effect of climate stress but might not be good enough to cover producers' financial losses due to severe weather. Policy makers might also consider introducing a weather index livestock insurance to mitigate producers' potential losses from severe weather.

Using individual carcass-level data, this study examined the influence of heat and cold stress on beef cattle production. The disadvantage of the packing plant data is that it does not contain climate data, which can be collected from feedlots through the installation of weather observation equipment. To overcome this shortcoming, weather data were obtained according to the location of each feedlot for six months before the processed date. This research also attempted to provide evidence that heat and cold stress caused economic losses because of a decline in meat productivity and quality. Furthermore, insurance premium rates were calculated to provide the basis for designing a weather index livestock insurance.

The quality of forage such as moisture, crude protein, and relative feed value also affects beef cattle productivity (Ball *et al.* 2001; Craine *et al.* 2010; Wheeler and Reynold 2013; Izaurralde *et al.* 2011) and is also sensitive to climate. According to Craine *et al.* (2010), forage quality was worsened by high temperature and low precipitation. It is also possible that severe weather condition for the period on grass of a calf could influence on beef cattle production through lowering forage quality. Past findings imply that climate stress directly aggravated the productivity of beef cattle and also indirectly worsened it by lowering forage quality. However, we had to leave these topics for future studies because we could not find proper proxies for forage quality.

Future studies can refine findings of this research by collecting data from both feedlots and packing plants. The feedlot data containing entry weight and the time of placement will help to measure the impact of severe weather on cattle performance more precisely. It is also critical to count death losses due to severe weather conditions in a feedlot to measure total losses. A packing plant data only contains the attributes of cattle which survived from severe weather conditions. Besides, it is better to know how producers mitigated weather stress in a feedlot. Producers' efforts to manage climate conditions could significantly influence carcass traits, especially under adverse weather conditions.

5. CONCLUSIONS

This dissertation investigates the present of grader bias in the U.S. beef grading system and the influence of weather stress on beef cattle production. First, we attempt to reveal the existence and possible sources of the bias in yield and quality grading. Second, the effect of heat and cold stress on beef cattle feedlot performance such as yield index, marbling score, ribeye area size, and fat thickness is examined.

In the grader bias analysis, we develop a behavior model to examine the existence and potential sources of grader bias in determining quality and yield grades of beef cattle carcasses. The results of the analysis show that USDA human graders' quality grading behavior was influenced by seasonality in Choice-Selected spread, the number of carcasses processed, and carcass characteristics. We also found that an economic event influencing producers' and packers' profit, graders' cognitive bias, and the low frequency of grading the extreme grades could influence USDA graders' yield grade grading. These findings support the USDA's plan of replacing more human graders with machine grading systems to enhance the accuracy and precision of the U.S. beef grading system.

In the weather stress analysis, we investigate how heat and cold stress influenced beef cattle performance. The results indicate that heat and cold stress deteriorated yield index (meat productivity), while marbling score (meat quality) was only worsened by cold stress. Simulation analysis is also conducted to reveal the impact of climate stress on the profitability of beef cattle producers. The simulation results show that producers' losses would increase as weather stress steadily rises. Given these results, we calculate fair premium rates of a weather-index livestock insurance to suggest a possible financial tool to mitigate producers' potential losses from weather stress.

Our study in this dissertation was conducted based on the data collected from limited regions and periods. The feedlot data were collected from a Midwest packing plant from 2005 through 2008. The results provided in this dissertation should be interpreted with caution. In addition, we could not conduct consumers' welfare analysis due to the lack of price information. Hence, future research could be conducted using nationally representative samples and additional market price information to investigate the impact of grader bias and weather stress on consumers' welfare along with the national level analysis of grader bias and weather stress in beef production.

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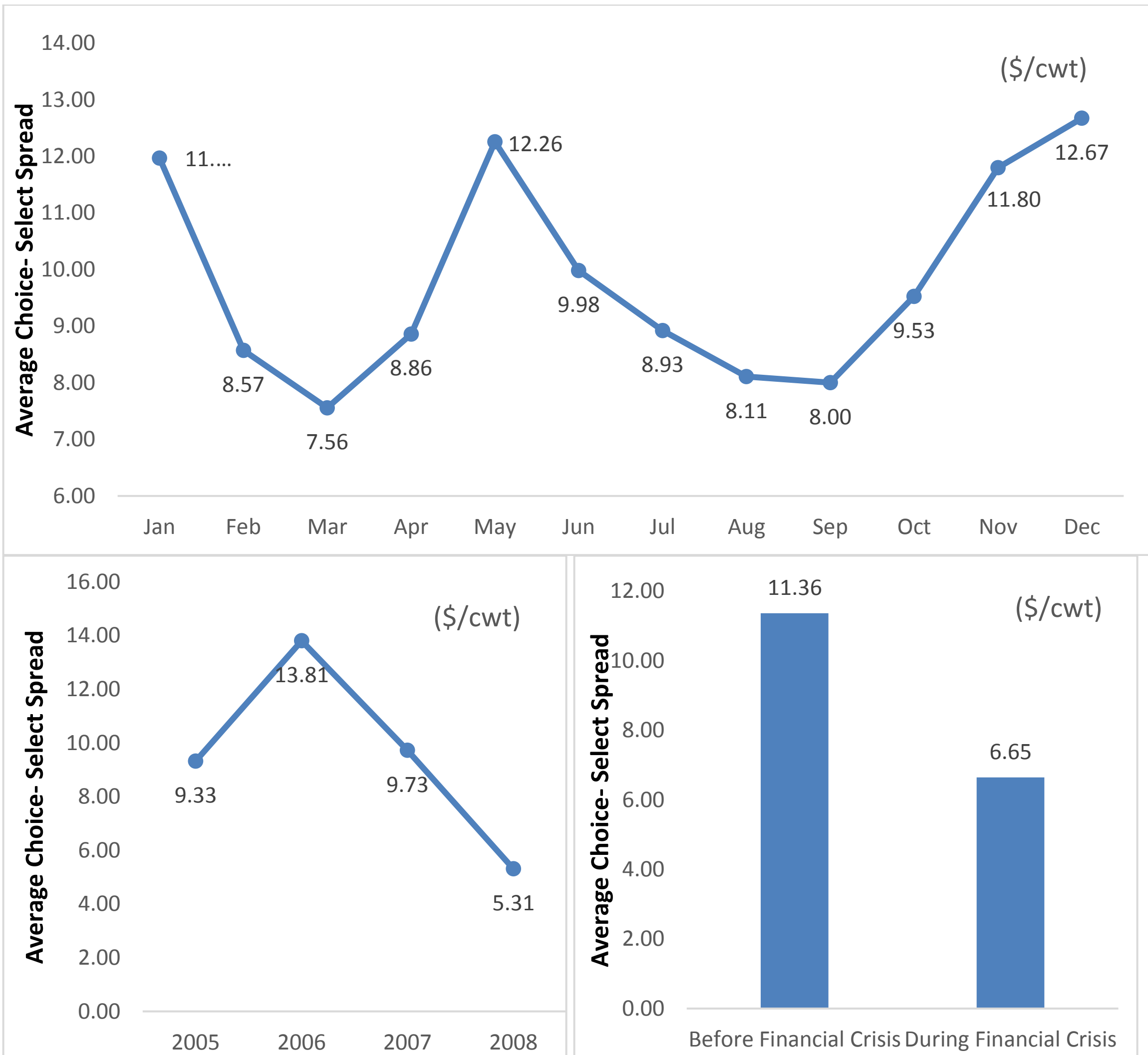
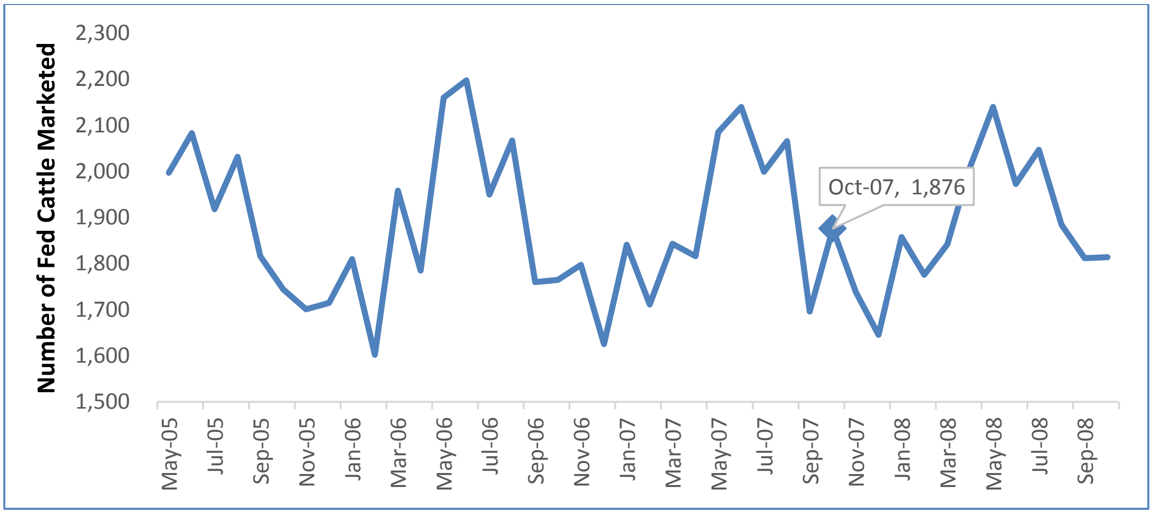
APPENDIX

FIGURES AND TABLES IN SECTION 2 THROUGH 4



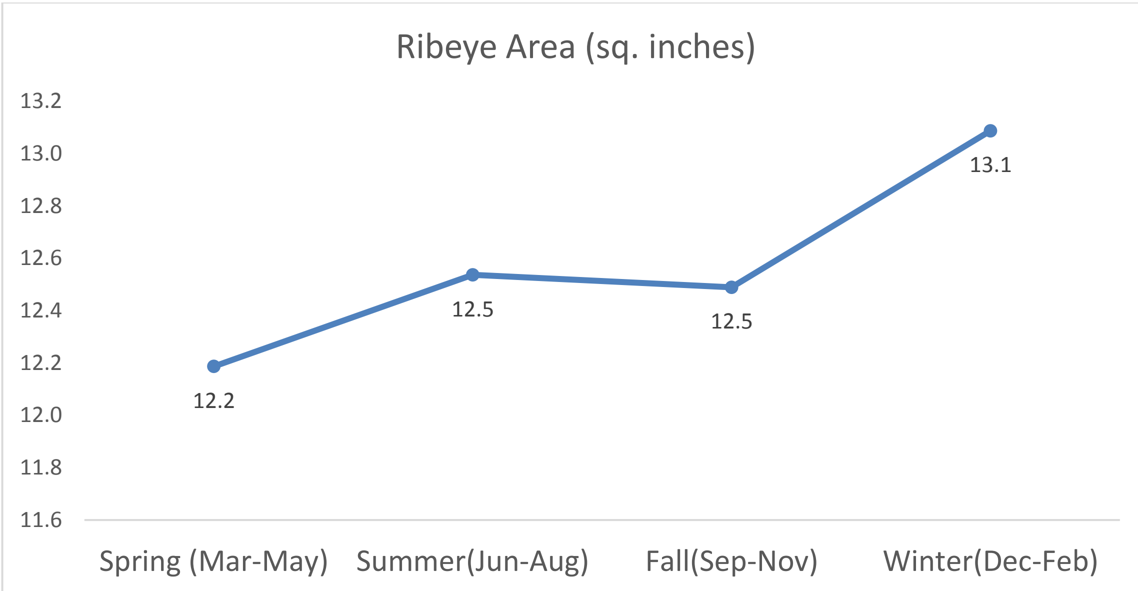
Source: USDA AMS 5-Area Weekly Direct Slaughter Reports

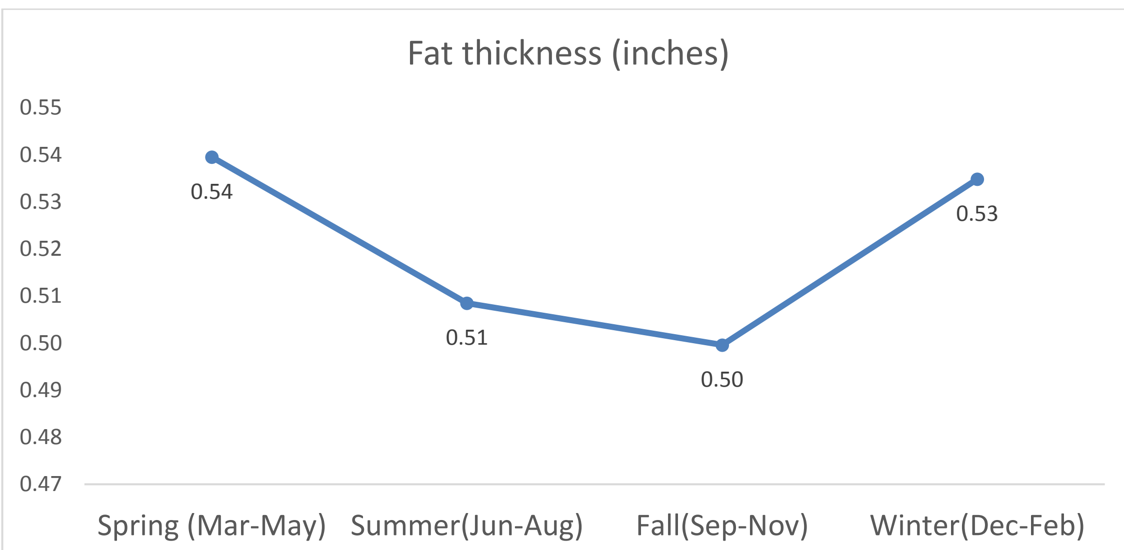
Figure A.1. Average Choice-Select Spread during our sample period (May 2005 – Oct 2008)



Source: USDA reports, Cattle on Feed
(http://usda.mannlib.cornell.edu/MannUsda/viewDocumentInfo.do?documentID=1020)

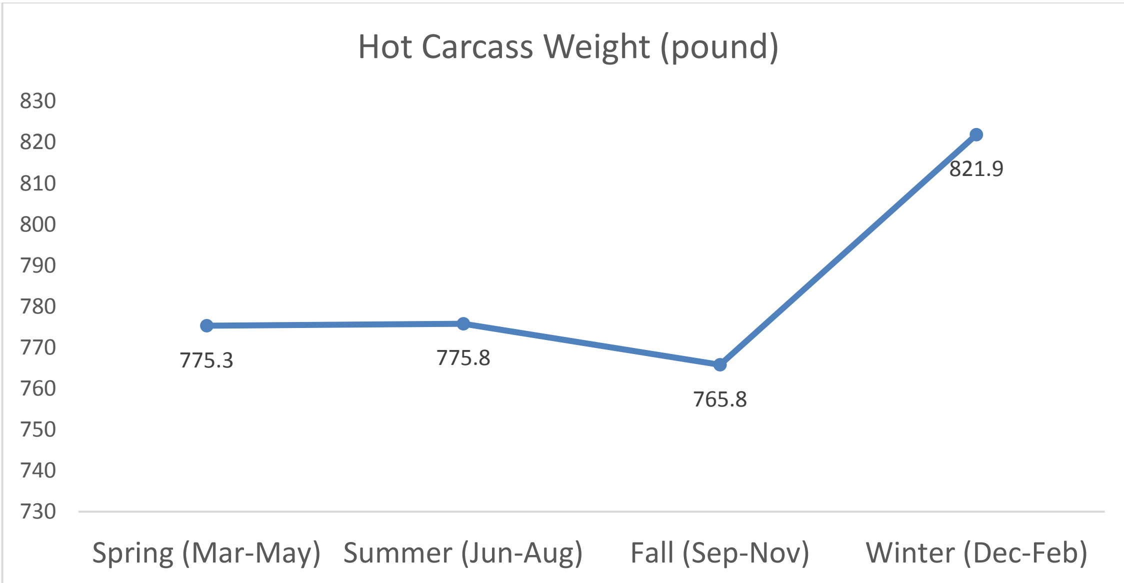
Figure A.2. Number of Fed Cattle Marketed on 1,000+ Capacity Feedlots – United States: May 2005 - October 2008 (Unit: 1,000 head)

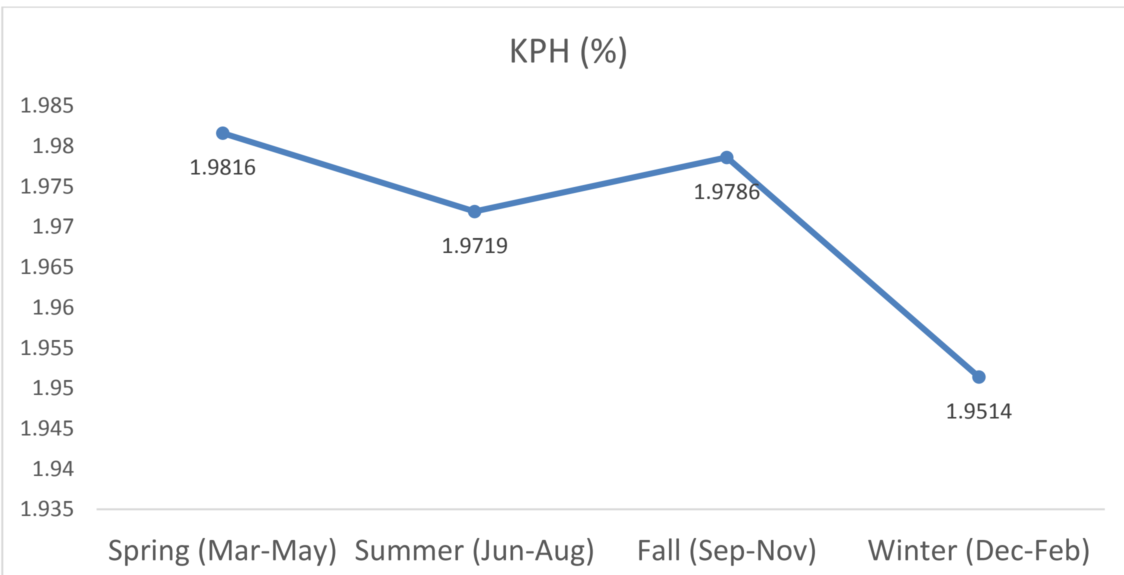




Source: Ribeye area and fat thickness were collected from a large-scale Midwest packing plant from May 2005 to October 2008.

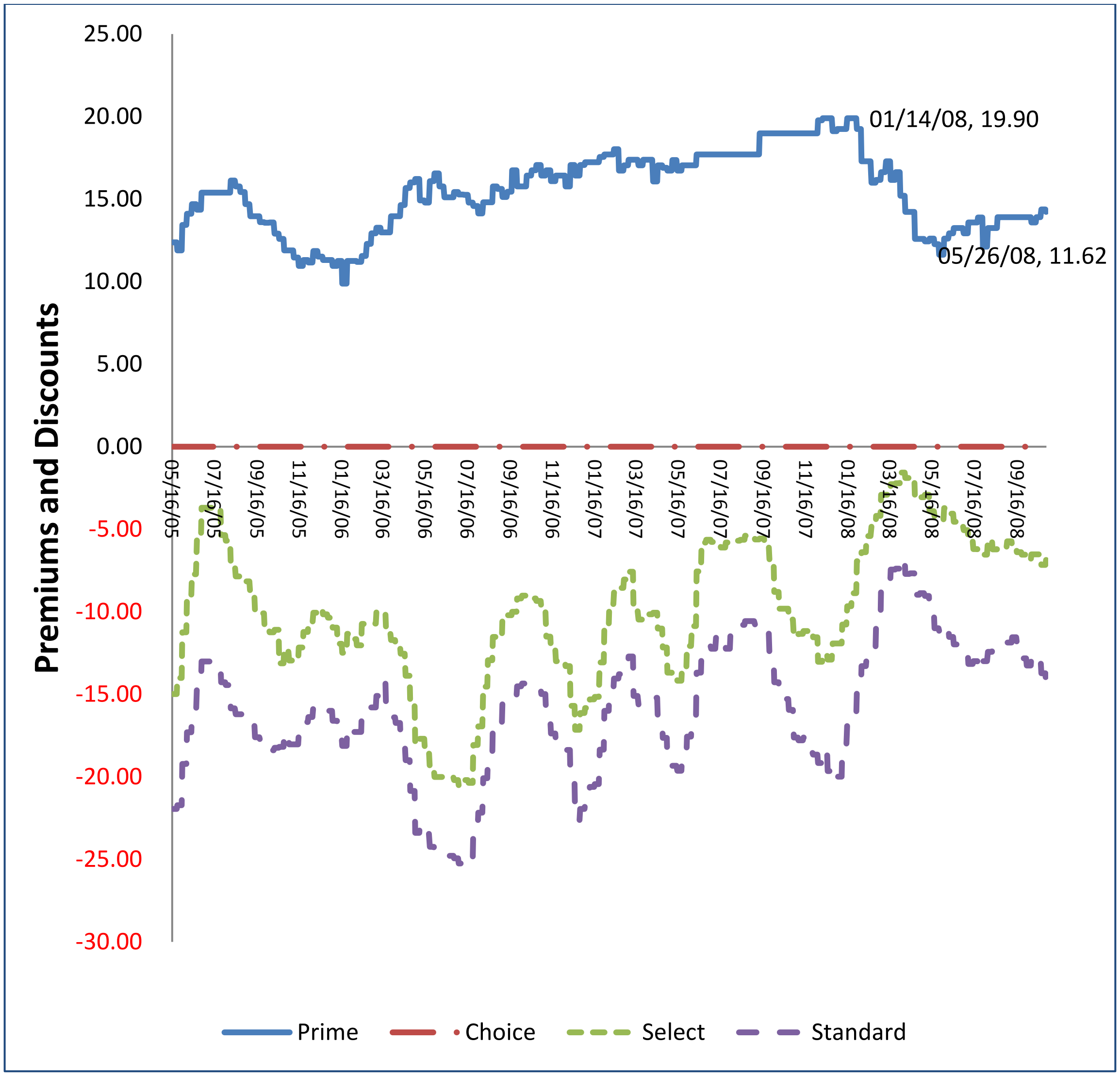
Figure A.3. Average Ribeye Area, Fat thickness, Hot Carcass Weight, and KPH (Seasonal, May 2005 – Oct 2008)





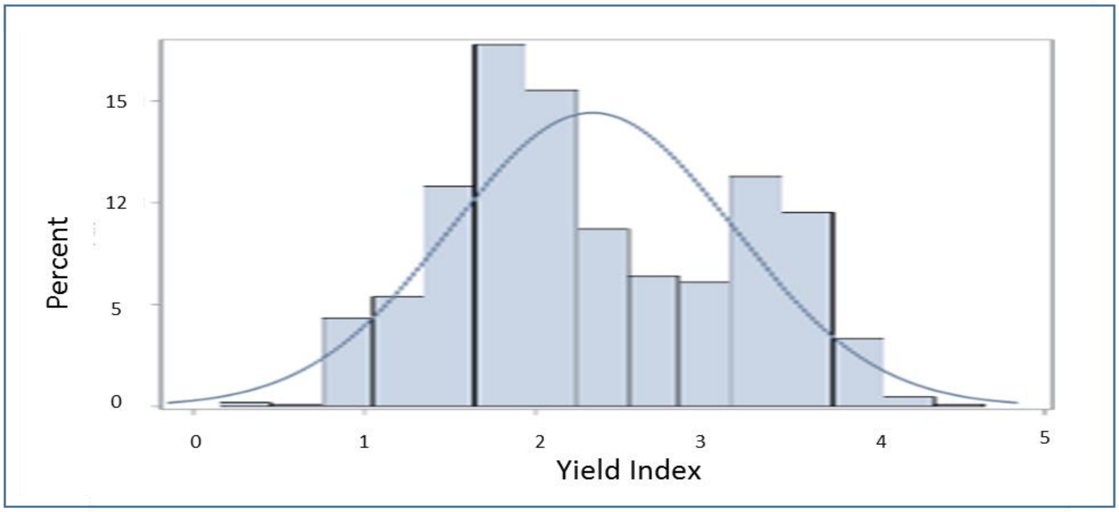
Source: Hot carcass weight and KPH (kidney, pelvic, and heart fat) were collected from a large-scale Midwest packing plant from May 2005 to October 2008.

Figure A.3. Continued

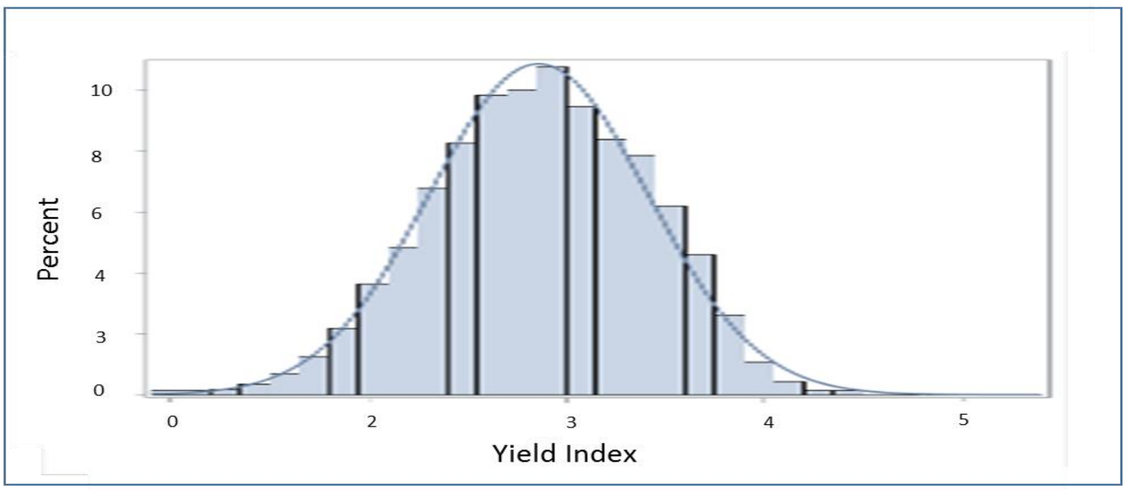


Source: USDA AMS 5-Area Weekly Direct Slaughter Reports

Figure A.4. Premiums and Discounts – Weekly Average Direct Beef carcasses ($ Per Cwt)



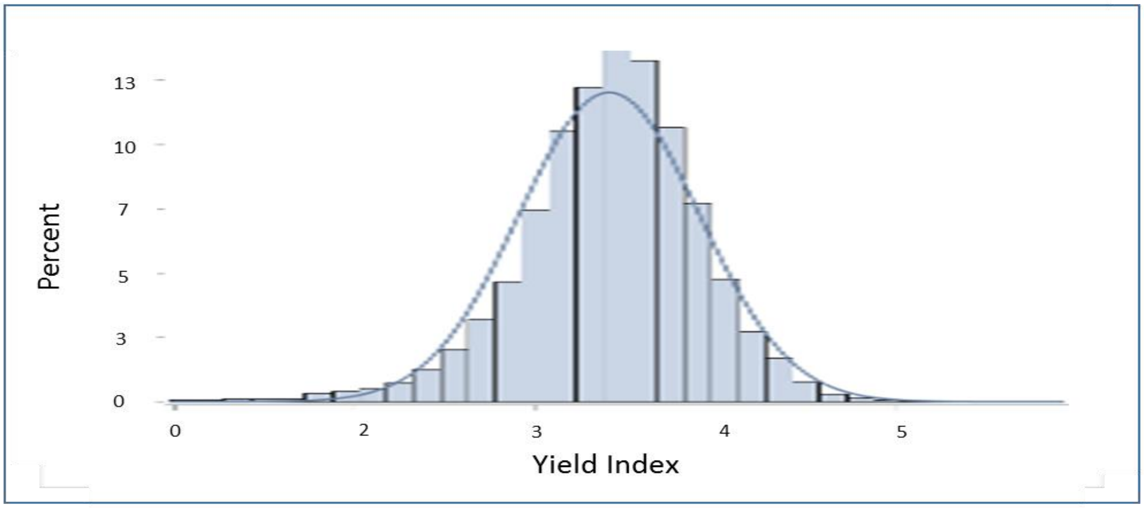
(Probability Distribution Function of Yield Index Given Human-graded Yield = 1)



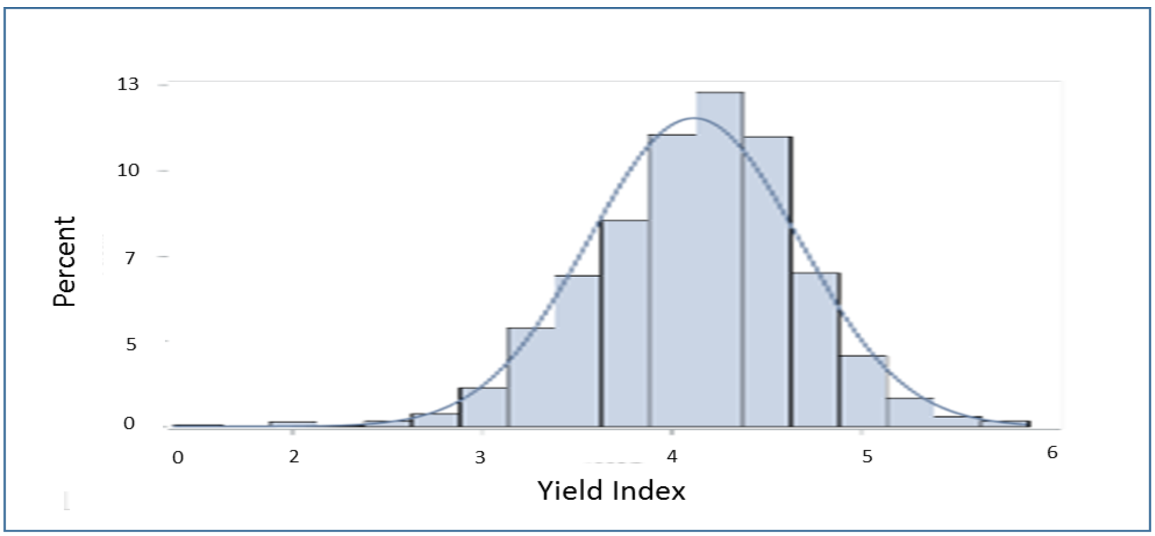
(Probability Distribution Function of Yield Index Given Human-graded Yield = 2)

Source: Yield grade (yield index) data were collected from a large-scale Midwest packing plant from May 2005 to October 2008.

Figure A.5. Probability Distribution Function (Normal Distribution) of Yield Index Given Human-graded Yield Grade



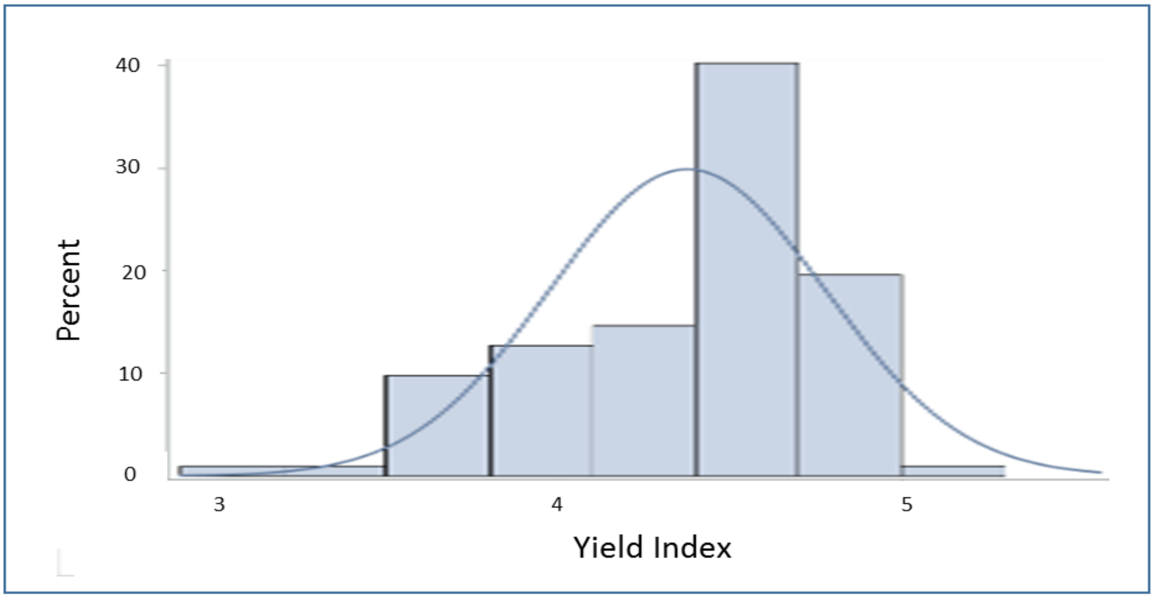
(Probability Distribution Function of Yield Index Given Human-graded Yield = 3)



(Probability Distribution Function of Yield Index Given Human-graded Yield = 4)

Source: Yield grade (yield index) data were collected from a large-scale Midwest packing plant from May 2005 to October 2008.

Figure A.5. Continued



(Probability Distribution Function of Yield Index Given Human-graded Yield = 5)

Source: Yield grade (yield index) data were collected from a large-scale Midwest packing plant from May 2005 to October 2008.

Figure A.5. Continued

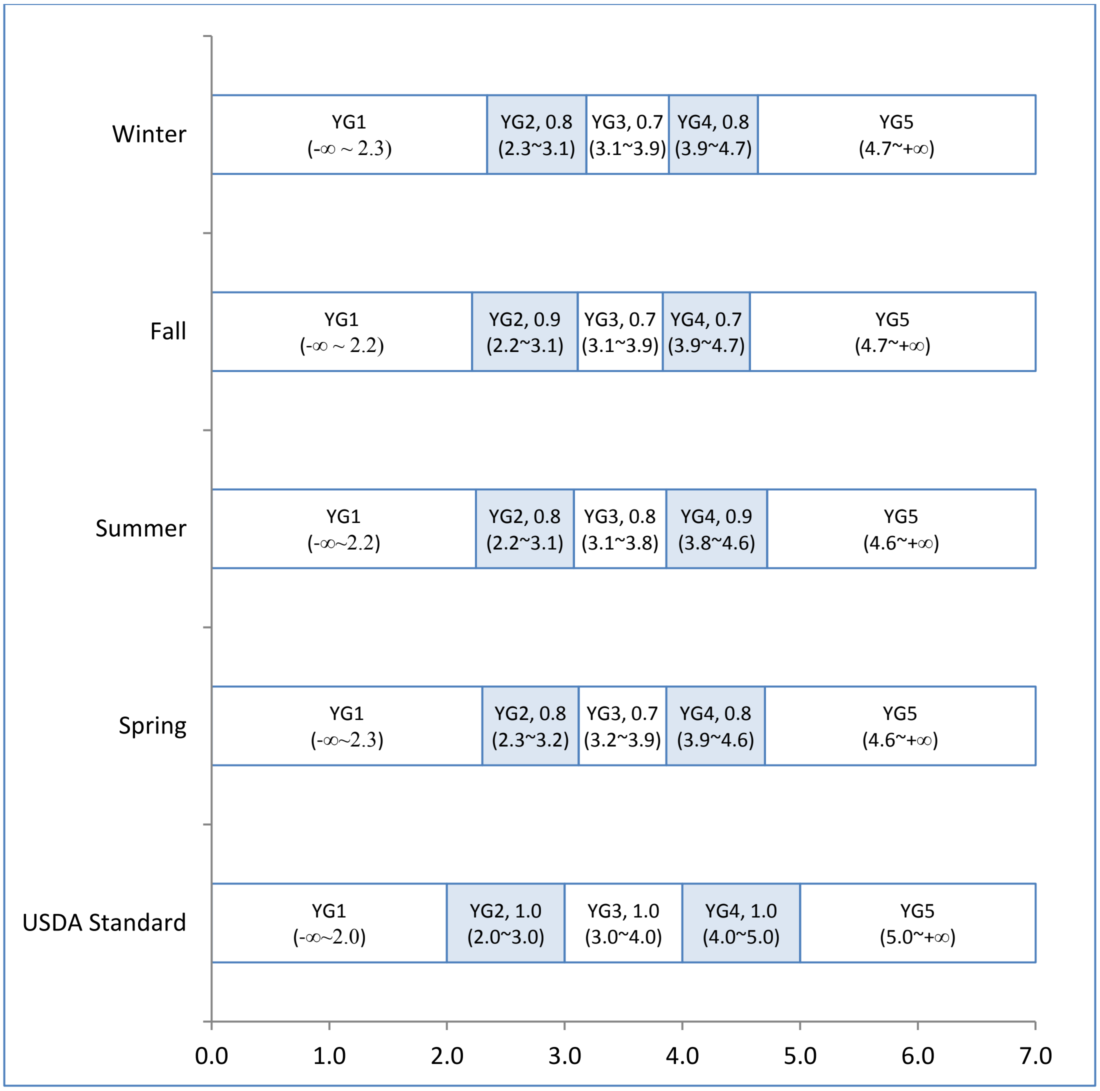


Figure A.6. Estimated and USDA Standard Intervals: Seasonal Analysis

Table A.1. The Means of Estimated Cutoff points and The Results of Hypothesis Tests Using Bootstrap Method

Period	$\hat{C}_1$	$\hat{C}_2$	$\hat{C}_3$	$\hat{C}_4$
Whole Sample Analysis				
Whole Sample	2.266*** (0.835)	3.090*** (0.762)	3.861*** (0.644)	4.689*** (0.629)
Hypotheses	$\hat{C}_1 = 2$	$\hat{C}_2 = 3$	$\hat{C}_3 = 4$	$\hat{C}_4 = 5$
Results : t-value (p-value)	402.1 (0.000)	208.4 (0.000)	-251.7 (0.000)	-313.4 (0.000)
Weekend Effect Analysis				
Weekday (Mon – Fri)	2.240** (0.971)	3.074*** (0.767)	3.842*** (0.631)	4.686*** (0.666)
Weekend (Sat - Sun)	2.414*** (0.574)	3.195*** (0.641)	4.009*** (0.684)	4.702*** (0.635)
Hypotheses	$\hat{C}^{weekday}{}_n = \hat{C}^{weekend}{}_n$ for n = 1, 2, 3, and 4			
Results : t-value (p-value)	-10.8 (0.000)	-126.2 (0.000)	-116.8 (0.000)	-5.7 (0.000)
Financial Crisis Analysis				
Before (May 2005 – Jul 2007)	2.305*** (0.907)	3.122*** (0.755)	3.887*** (0.644)	4.711*** (0.763)
During (Aug 2007 –Oct 2008)	2.023*** (0.757)	2.898*** (0.857)	3.644*** (0.812)	4.617*** (0.989)
Hypotheses	$\hat{C}^{before}{}_n = \hat{C}^{during}{}_n$ for n = 1, 2, 3, and 4			
Results: t-value (p-value)	201.0 (0.000)	241.1 (0.000)	161.1 (0.000)	13.25 (0.000)

Note: Standard errors in parentheses; '***', '**', and '*' represent significance at 0.01, 0.05, and 0.1 levels, respectively. $\hat{C}_k$ for k = 1, 2, 3, and 4 is an estimated cutoff point for each yield grade and is defined in the equation (9).

Table A.1. Continued

Period	$\hat{C}_1$	$\hat{C}_2$	$\hat{C}_3$	$\hat{C}_4$
Corn Price Analysis				
Before	2.343***	3.152***	3.884***	4.690***
(May 1, 2005 – Jan 1, 2007)	(0.847)	(0.742)	(0.587)	(0.660)
After	2.180***	3.021***	3.831***	4.707***
(Jan 2, 2007 – Oct 31, 2008)	(0.671)	(0.600)	(0.710)	(0.566)
Hypotheses	$\hat{C}^{before}{}_n = \hat{C}^{after}{}_n$ for n = 1, 2, 3, and 4			
Results	142.5	193.1	49.6	8.1
	(0.000)	(0.000)	(0.000)	(0.000)
Feed Ratio Analysis				
Before	2.348***	3.159***	3.882***	4.691***
(May 1, 2005 – Nov 1, 2006)	(0.850)	(0.755)	(0.583)	(0.666)
After	2.187***	3.024***	3.833***	4.704***
(Nov 1, 2006 – Oct 31, 2008)	(0.664)	(0.604)	(0.711)	(0.561)
Hypotheses	$\hat{C}^{before}{}_n = \hat{C}^{after}{}_n$ for n = 1, 2, 3, and 4			
Results	132.5	186.7	-46.6	-6.4
	(0.000)	(0.000)	(0.000)	(0.000)
Workload Analysis				
May - August	2.270***	3.080***	3.867***	4.699***
	(0.763)	(0.739)	(0.674)	(0.623)
Other months	2.229**	3.108***	3.856***	4.646***
	(0.120)	(0.793)	(0.595)	(0.764)
Hypotheses	$\hat{C}^{May-Aug}{}_n = \hat{C}^{Others}{}_n$ for n = 1, 2, 3, and 4			
Results	22.4	-30.9	10.3	11.8
	(0.000)	(0.000)	(0.000)	(0.000)

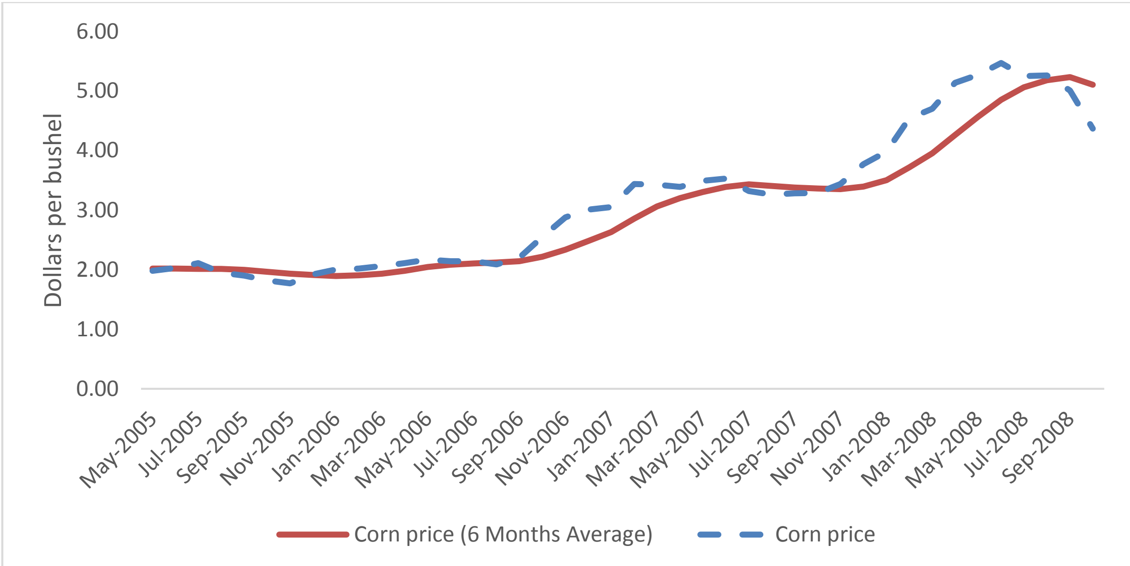
Note: Standard errors in parentheses; '***', '**', and '*' represent significance at 0.01, 0.05, and 0.1 levels, respectively. $\hat{C}_k$ for k = 1, 2, 3, and 4 is an estimated cutoff point for each yield grade and is defined in the equation (9).

Table A.1. Continued

Period	$\hat{C}_1$	$\hat{C}_2$	$\hat{C}_3$	$\hat{C}_4$
Seasonal Analysis				
Spring	2.299*** (0.755)	3.113*** (0.705)	3.857*** (0.587)	4.698*** (0.539)
Summer	2.258*** (0.854)	3.070*** (0.730)	3.871*** (0.746)	4.686*** (0.760)
Fall	2.200** (1.144)	3.101*** (0.859)	3.862*** (0.629)	4.693** (3.589)
Winter	2.404* (3.598)	3.186** (1.059)	3.889*** (0.667)	4.784 (11.563)
Hypotheses	$\hat{C}^{Season1}{}_n = \hat{C}^{season2}{}_n$ for n = 1, 2, 3, and 4			
Cutoff points for each season	$\hat{C}^{Spring}{}_1$	$\hat{C}^{Summer}{}_2$	$\hat{C}^{Fall}{}_3$	$\hat{C}^{Winter}{}_4$
$\hat{C}^{Spring}$	-	53.3 (0.000)	0.2 (0.834)	5.6 (0.000)
$\hat{C}^{Summer}$	27.9 (0.000)	-	-0.4 (0.725)	6.2 (0.000)
$\hat{C}^{Fall}$	43.9 (0.000)	-20.8 (0.000)	-	0.9 (0.890)
$\hat{C}^{Winter}$	-5.5 (0.000)	-24.3 (0.000)	-0.8 (0.421)	-

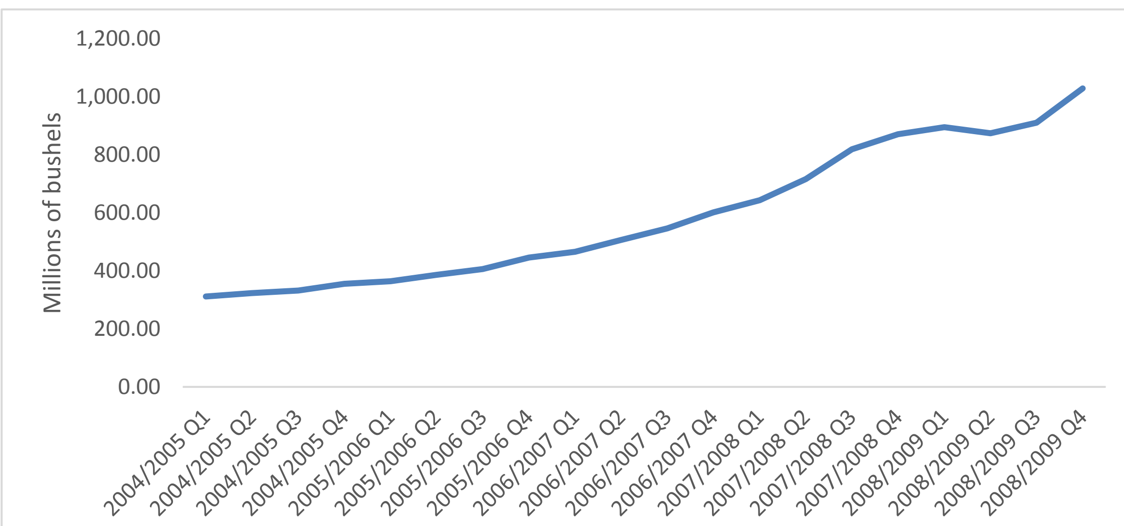
Note: Standard errors in parentheses; '***', '**', and '*' represent significance at 0.01, 0.05, and 0.1 levels, respectively. $\hat{C}_k$ for k = 1, 2, 3, and 4 is an estimated cutoff point for each yield grade and is defined in the equation (9).

Panel A. Corn Prices, May 2005 – October 2008



Source: USDA ERS

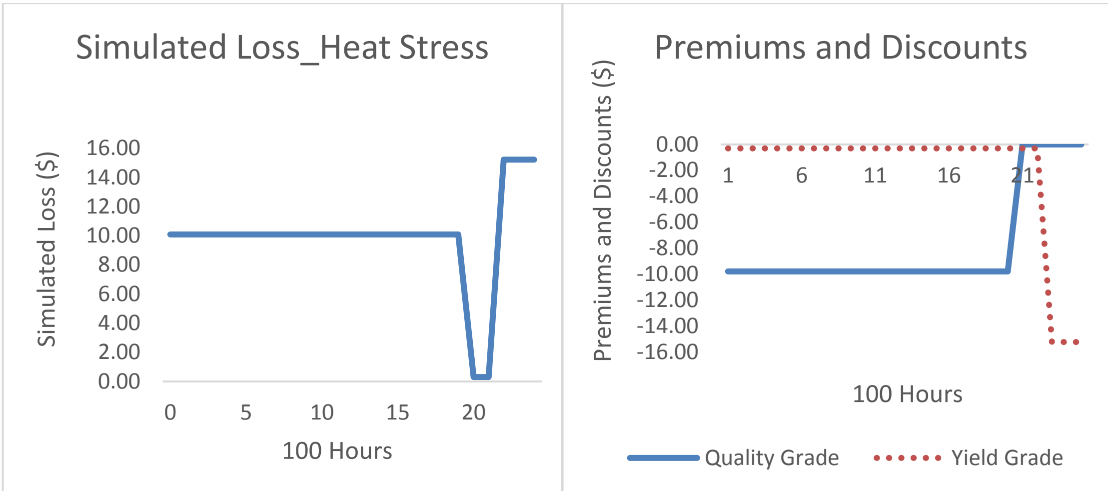
Panel B. Corn Uses for Ethanol Production, September 2004 – August 2008



Source: USDA ERS

Figure A.7. Corn Prices and Corn Uses for Ethanol Production.

Panel A. Heat Stress



Panel B. Cold Stress

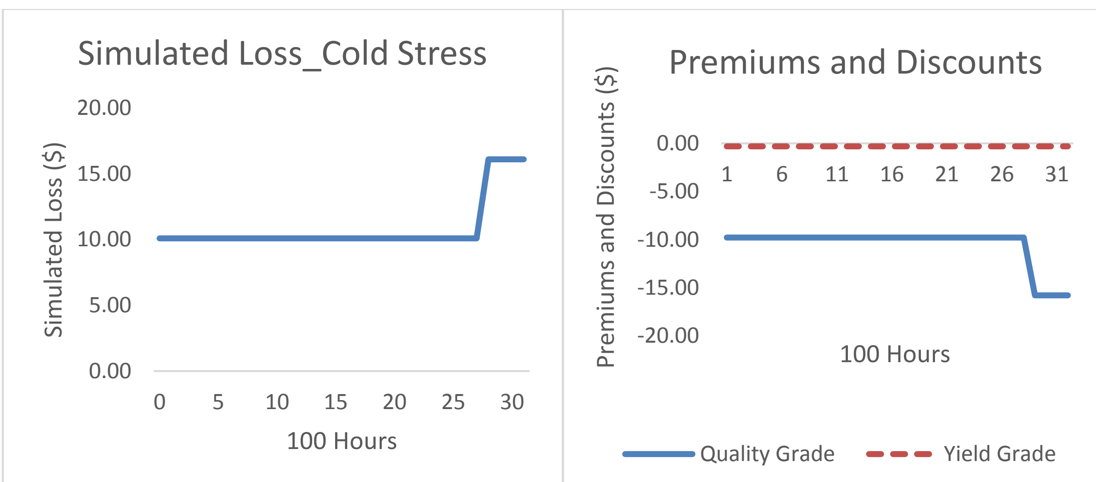
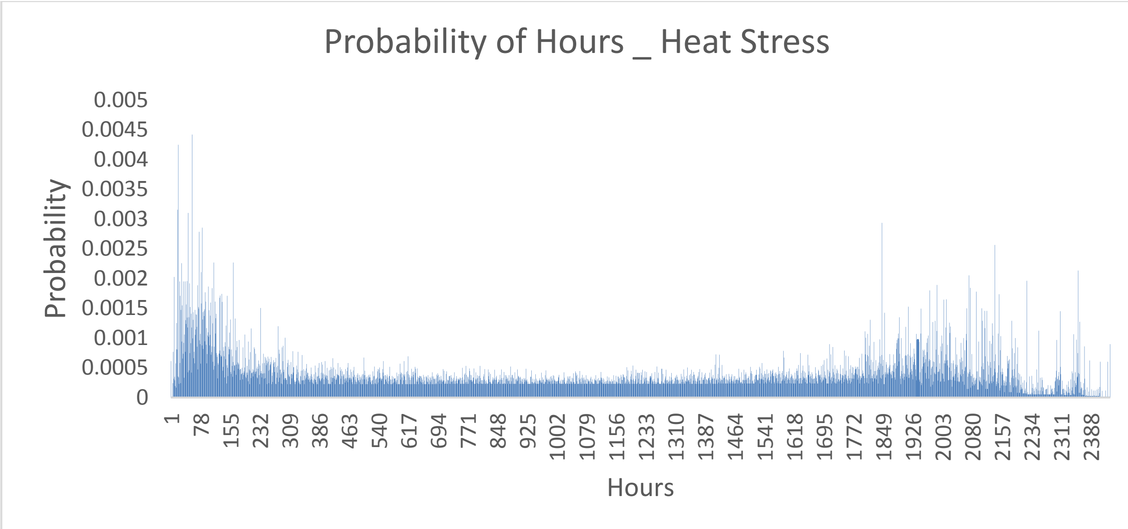


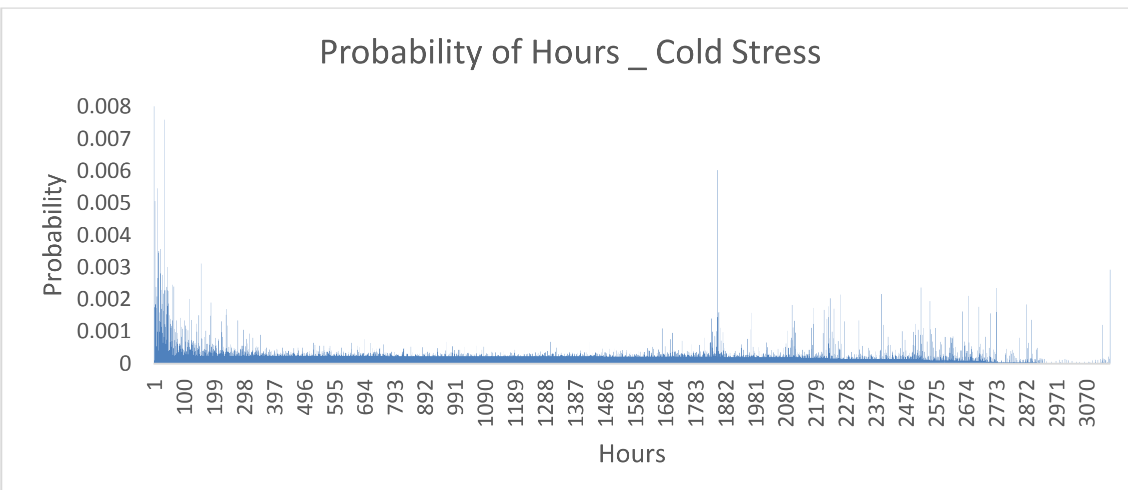
Figure A.8. Simulated Loss and Premiums/Discounts across Hours Exposed to Weather Stress

Note: The maximum hours exposed to heat (cold) stress in this figure was restricted as historical maximum hours exposed to heat (2,437 hours) and cold (3,148 hours) stress in Figure A.9 to guarantee the feasibility of weather stress range.

Panel A. Heat Stress



Panel B. Cold Stress



Source: The weather data (ambient temperature, relative humidity, wind speed, and solar radiation) for computing hours exposed to heat and cold stress data were collected from National Renewable Energy Laboratory.

Figure A.9. Probability (Density) of Heat and Cold Stress Exposure Hours in Eastern Nebraska Location, 1998-2015

Table A.2. Premiums Related to Various Heat and Stress Strike Levels

Panel A. Heat Stress

Strike	Strike Percentile	Premium ($/cwt)	Premium ($/head)
1,500	62.1	0.11	0.86
1,600	65.6	0.10	0.78
1,700	69.1	0.09	0.70
1,800	73.1	0.08	0.61
1,900	78.8	0.06	0.48
2,000	85.1	0.05	0.34

Note: Premium for per head was calculated based on the assumption that the weight of beef cattle is 750 pounds

Panel B. Cold Stress

Strike	Strike Percentile	Premium ($/cwt)	Premium ($/head)
2,000	74.3	2.60	19.46
2,100	77.1	2.31	17.35
2,200	80.4	1.98	14.84
2,300	84.1	1.60	12.03
2,400	86.4	1.38	10.31
2,500	89.0	1.11	8.36

Note: Premium for per head was calculated based on the assumption that the weight of beef cattle is 750 pounds