Searching for the Possible Sources of Grader Bias in Beef Grading: A Non-parametric Approach

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ABSTRACT

Because grading errors can impede the integrity of the beef grading system, it is important to investigate the existence and possible sources of grader bias. In this article, we use a non-parametric method to identify grader bias in the beef grading system. Using simulation studies, we show that this method performs well without the normal distribution assumption. We find that macroeconomic events and graders' mood may affect grades using a non-parametric method. Further, the premium/discount analysis in this article suggested that, under the grid price system, livestock producers could have lost financially if human graders had been replaced by camera-grading system during our sample period.

Key words: Grader bias, Yield grade, Beef grading system, Non-parametric cutoff point estimation.

The U.S. beef grading system plays an important role in facilitating beef marketing and promoting beef quality. In spite of the grade's importance USDA graders must visually inspect and "call" the grade of a carcass within a few seconds. In this circumstance, the occurrence of grading errors is inevitable. These errors reduce incentives to produce high-quality product (Chalfant *et al.* 1999) and decrease the efficiency of the marketing process.

The most relevant article on this topic is Hueth, Marcoul, and Lawrence (2007). Their research objective was to determine if grader bias[1] exists by testing the distributions between called and true grades. This paper extends and builds upon the inquiry of Hueth, Marcoul, and Lawrence (2007) with major departures. First, the assumption of normality is relaxed using a non-parametric approach that allows working with various probability distributions. The normal distribution assumption can critically affect model estimation because their models directly use the cumulative distribution function of the standard normal to estimate the grade category cutoff points. Moreover, the data indicates that "measured" yield grade distributions given "called" yield grades for yield grade 1 and 5 do not follow the normal distribution. This implies that a parametric method with the normal distribution assumption inconsistently estimates cutoff points. In this article, a non-parametric method is used to estimate cutoff points more consistently. Using simulation methods, we attempt to demonstrate that a non-parametric method performs well without the normal distribution assumption.

[1] In the literature, the term "grader bias" refers to grading errors, not to imply that graders are "biased" for or against any party in the transaction.

Second, we further extend Hueth, Marcoul, and Lawrence (2007) by identifying possible sources of grader bias by comparing grading patterns across time. We hypothesize that economic factors and graders' mood are attributable to grading behavior. Yield grade, which represents cutability of beef carcasses, has an effect on beef price in grid pricing mechanisms, so it is possible that economic situations could influence grading behavior. In addition, graders are human beings, and thus mood can potentially influence their judgment and grading behavior.

One of the major economic events during our sample period (2005-2008) is the financial crisis in 2008. U.S. per capita beef consumption declined in 2008 presumably due, in part, to the income effects of the financial crisis. Since beef price does depend on the grade called by the USDA graders, we hypothesize that the financial crisis may have affected the grader's called grades. Given this expectation, we examine the difference of grading patterns before/during financial crisis to investigate how the economic recession may have affected beef grading. If different grading behaviors were found during the financial crisis, a reasonable hypothesis might conclude that the crisis is one possible source of grader bias. This investigation provides evidence on the impact of macroeconomic events on beef grading.

Yield grade reflects the amount of lean meat from a carcass, indicating that feed quality and feed intake of slaughter cattle influence the yield grade. The increasing production and use of ethanol in the U.S. and increasing feed demand from Asia, led to dramatic increases in the price of feed in late 2006 through the first half of 2008. Figure 1 contains the U.S. average price received for corn over the study period, illustrating the feed price increase. Because the price of corn and cattle, and later beef with a time lag, move in opposite directions: beef prices decrease in the short term as the corn price increases while increasing in the longer term, producers sell off their cattle when higher feed prices erode profits (Hebert and Anderson 2011). Higher feed costs may prompt cattle feeders to decide to sell their cattle at lighter weights before they reach a maximum level of fatness. Early processed cattle, thus, may have less fat, or finish, on them (weight). Since the primary factor that determines yield grade is fatness, yield grade is often lower when producers sell off cattle early. Graders may be intuitively aware of feeder's early sales when corn price increases. This prior belief of graders might lead them to call a lower grade than measured grade. It might be reasonable to expect that USDA graders called lower yield grades after corn prices increased.

Graders' mood can be another source of the grader bias. Existing literature on psychology supports the existence of weekly cyclicity in mood among working adults. Specifically, mood is more positive on weekends, than the rest of the week, and Monday's mood is worse than that of other days of the week (Ryan, Bernstein, Brown 2010). Graders' changes in mood during the week can lead to regular week patterns in grader bias. Ryan, Bernstein, and Brown (2010) found that well-being of a worker, both men and women, is significantly higher from Friday evenings through Sunday afternoon. Similar evidence was found in existing literature in finance, which is called "weekend effect." This effect has been used to explain why stock markets open lower on Monday than they closed the previous Friday. If this type of the weekend effect exists in beef grading, USDA graders' mood might generate different patterns on a specific weekday. From these previous findings, we expect that USDA graders will grade a beef carcass stricter in the beginning of the week compared to other days of the week.

Since USDA is currently researching and employing the use of camera-grading systems with the hope to fully adopt them in the future, it is worth analyzing the effect of shifting from USDA graders to camera-grading on producers and packers. To predict the possible effects of the policy change, it is meaningful to measure financial gains/losses of producers and packers from the reduced use of USDA graders. If grading errors are systematically biased, one of two groups will have a financial advantage from their cattle transactions when the new policy is implemented. For instance, if USDA graders tend to call higher yield grade than grades assigned by camera then packers will benefit financially, when USDA graders replaced by a cameras.

To our knowledge, this is the first study investigating the existence and possible sources of grader bias using a non-parametric approach. As shown in our simulation exercise, the non-parametric estimation approach allows the estimation of yield grade category cutoff points more accurately. Large sample size and multiple years of data allows the investigation of grading behavior comparing grading patterns across time.

How to measure USDA yield grade

USDA yield grade represents beef carcass cutability, which means an estimate of the amount of lean, edible meat from a carcass (Field 2007). USDA yield grade consists of five grades: yield grade 1, yield grade 2, yield grade 3, yield grade 4, and yield grade 5. A lower USDA yield grade number is generally better, because it represents a higher yield of edible meat. The determinants of the USDA yield grade are (1) external fat thickness over ribeye; (2) ribeye area; (3) estimated percentage of kidney, pelvic and heart fat; and (4) hot carcass weight. The equation for determining USDA yield grade is as follows:

(1) 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. If yield index is strictly less than 2.0, then yield grade is 1; if yield index is between 2.0 and 2.99 then yield grade is 2; if yield index is between 3.0 and 3.99 then yield grade is 3; if yield index is between 4.0 and 4.99 then yield grade is 4; and 5 otherwise. USDA graders may use this equation in commercial practice, but his/her decisions are usually based on their prior training and experience.

Model

Let $\mathrm{I_k}$ be the interval for yield grade k. These grade intervals allow the expression of yield grade as a function as follows:

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

According to the USDA standards, the USDA Standard 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 $\hat{\mathrm{I}}_5 = [5.0,\ +\infty)$. The $\hat{\mathrm{I}}_1$ means that USDA graders should call yield grade 1 when an observed yield index is smaller than 2.0. Other yield grades should be called in a similar way, in that a grade is "called" when yield index falls within the indicated range.

Our data sample indicates that "called" yield grade is not identical with "measured" yield grade; therefore, we presume that USDA graders can have different yield index intervals than the USDA standards. Using this premise, USDA grader's intervals ($\tilde{I}_k$) are defined with implicit cutoff points (C_k, $k = 1, 2, 3, 4$, and 5) such as $\tilde{I}_1 = (-\infty, C_1)$, $\tilde{I}_2 = [C_1, C_2)$, $\tilde{I}_3 = [C_2, C_3)$, $\tilde{I}_4 = [C_3, C_4)$, $\tilde{I}_5 = [C_4, +\infty)$. We also define c_i as "called" yield grade and m_i as "measured" yield grade for a carcass i.

If these implicit cutoff points are different from the USDA standards across time then we can conclude grader bias exists and grading errors are systemically biased across time.

The kernel method is a non-parametric method that uses a smoothing kernel function in the empirical cumulative density functions. To apply a non-parametric method in our study, we use the empirical cumulative density functions: $F_k(C_h) = \frac{1}{n_k} \sum_{i=1}^{n_k} \Omega_k\left(\frac{C_h - m_i}{h_k}\right)$, k = 1, 2, 3, 4, and 5, where $\Omega_k(\ )$ is the Gaussian kernel function. Following Silverman (1986), Fluss, Faraggi, and Reiser (2005), the bandwidths, $h_k = 0.9 \min\left\{\frac{s_k,\ iqr_k}{1.34}\right\} n_k^{-0.2}$, k = 1, 2, 3, 4, and 5, is used to manage the amount of smoothing, where s_k is the standard deviation and iqr_k is the inter quartile range of the sample.

The likelihood function for our non-parametric model that allows us to estimate graders' implicit beliefs is defined as follows:

$$L\left(c_j, m_j \mid C_1^{np}, C_2^{np}, C_3^{np}, C_4^{np}\right) = \mathbf{1}\left(c_j = 1\right) F_1\left(C_1^{np}\right)$$
$$\times \prod_{k=1}^{3} \mathbf{1}\left(c_j = k\right)\left[F_{k+1}\left(C_{k+1}^{np}\right) - F_k\left(C_k^{np}\right)\right] \times \mathbf{1}\left(c_j = 5\right)\left[1 - F_5\left(C_4^{np}\right)\right],$$

where, $C_k^{np}, k \in \{1, 2, 3, 4\}$ are parameters to be estimated, 1 ( ) is an indicator function, and $F_j(\ )$, j = 1, 2, 3, 4, and 5, are empirical cumulative density functions for each yield grade.

More accurate estimates of yield grade intervals are expected with this non-parametric method. Figures 3 and 4 contain the distributions of “measured” yield grade given “called” yield grades. Yield grades 1 and 5 are different from the normal distribution. The difference from the normal distribution affects the estimation because the shape of cumulative density function directly affects the estimation results in the model. A simulation model is employed to illustrate the effect of the non-parametric method.

Simulation Studies

To evaluate the performance of the non-parametric method, we estimated the implicit cutoff points with various distributions of “measured” yield grade given “called” yield grade 1:

(1) the normal distribution with mean 2, and standard deviation 0.5, N (1.5, 0.5),

(2) the log-normal distribution with location 1.5, and scale 0.5, LN (1.5, 0.5),

(3) the normal distribution with mean 2, and standard deviation 0.5, N (2.0, 0.5), and

(4) the normal distribution with mean 1.5, and standard deviation 1.0, N(1.5, 1.0).

The distributions of conditional “measured” yield grade 2, 3, 4, and 5 follow the normal distribution with its own mean and standard deviation, while the distribution shape of conditional “measured” yield grade 1 varies as shown above. Due to this standardized and consistent data generation procedure, the consistency of the non-parametric method can be evaluated through finding the difference between the true (C_1) and estimated ($\hat{\mathrm{C}}^{np}{}_1$) cutoff points. It is a well-known fact that non-parametric methods do not perform well with small sample size. Hence, the estimation is conducted for various sample sizes

(50, 100, 500, and 1,000 for each yield grade) to evaluate the impact of a sample size on the non-parametric estimation.

Simulations with normal distribution N (1.5, 0.5)

To conduct the simulation study, data for all conditional "measured" yield grades was generated. Each of the conditional "measured" yield grades in the generated data follows the normal distribution with mean k + 0.5, and standard deviation 0.5, where k = 1, 2, 3, 4, and 5. Given these distributions, the true cutoff point between yield grade 1 and 2 (C_1) should be 2.000 in our model because the distributions of yield grade 1 and 2 follow the normal distribution with mean 1.5, and 2.5, while the standard deviations for each distribution are identical as 0.5. Similarly, the true cutoff point for yield grade 2, 3, and 4 (C_2, C_3, and C_4) are 3.000, 4.000, and 5.000 respectively. Thus, the true cutoff points in this study are identical to the USDA standard cutoff points.

The simulation results from the non-parametric method in Table 1 show that estimated cutoff points, 2.050, 2.965, 3.968 and 4.994, are close to the true cutoff points, 2.000, 3.000, 4.000, and 5.000. The results also show that the accuracy of estimation increases as the sample size increases. It is clear from the above results that non-parametric method produce consistent results with the normal distribution.

Simulations with lognormal distribution LN (1.5, 0.5)

In this section, the distribution of "measured" yield grade given "called" yield grade 1 follows the lognormal distribution with location 1.5 and scale 0.5. Other distributions of conditional measured yield grades follow the normal distribution with their own mean, k + 0.5, k = 2, 3, 4, and 5, and standard deviation, 0.5. Unfortunately, we cannot specify the true cutoff point between yield grade 1 and 2 with the lognormal distribution. The lognormal distribution, however, has a thinner tail than the normal distribution. Thus, the true cutoff point between yield grade 1 and 2 should lesser than 2.000.

The results in Table 2 present that the estimated cutoff point between yield grade 1 and 2 ($\hat{C}_1^{np}$), 1.907, is close to 1.900 instead of 2.000. This finding suggests that a non-parametric method performs well when the distribution of "measured" yield grade do not follow the normal distribution.

Simulations with normal distribution N (2.0, 0.5)

We generated the data of "measured" yield grade given "called" yield grade 1 from the normal distribution with mean 2.0 and 0.5 in this section. Since the mean of the produced data are changed from one to two, we expect the estimated cutoff point between yield grade 1 and 2 is larger than 2.000. The simulation results in Table 3 indicate that the cutoff point from the non-parametric method, 2.268, is greater than the one from the simulation study with N (1.5, 0.5), 2.050. This difference implies that the non-parametric method performs better in reflecting the distribution shape into the estimation.

Simulations with normal distribution N (1.5, 1.0)

To examine the impact of various standard deviations on the estimation, we generate data follows normal distribution with mean 1.5 and standard deviation 1.0. The estimated cutoff point between yield grade 1 and 2 from the simulation study with N (1.5, 1.0), 1.854, is less than the one from the simulation study with N (1.5, 0.5), 2.050. These results also imply that the non-parametric method more sensitively reflects the distribution shape of the estimation.

Data

Data used in the section is from a large-scale Midwest packing plant for the period 2004 through 2008. There are two different yield grades for the same beef carcasses. One is yield grade called by USDA graders and the other is yield grade measured by camera. As illustrated in Figure 6, the distribution of called and measured yield grade is not identical. The difference between these two yield grades allows us to estimate graders' implicit cutoff values for each grade.

Results

In this section, we present the estimation results of the whole sample analysis, annual analysis, seasonal analysis, and weekly analysis to show how the economic and psychological factors are attributable to grading behavior.

Whole Sample Analysis

Table 5 contains the estimation results of the whole sample analysis. The results suggest that the intervals for yield grade 2, 3, and 4 are narrower than the intervals of the USDA standard, while the intervals for yield grade 1 and 2 are wider than intervals of the USDA standards. As illustrated in Figure 7, the cutoff point between yield grade 1 and 2 (4 and 5), 2.260 (4.693), is significantly greater (less) than the one of the USDA standard, 2.000 (5.000) while other cutoff points between yield grade 3 and 4, and 4 and 5 (3.094, 3.863) are similar with those of the USDA standard (3.000, 4.000). These results imply the existence of grader bias in our sample. Further, the outcome is also consistent with the expectation that graders make more mistakes when calling carcasses that “look bad or good”.

Annual Analysis

Table 6 and Figure 8 contain the estimated results of the annual analysis. The results indicate that the intervals for yield grade 1 have been getting narrower since 2006. Especially after 2007, the interval for yield grade 1 became significantly narrower. Specifically, the estimated interval for yield grade 1, $(+\infty, 2.276]$, in 2007 and became $(+\infty, 1.975]$, in 2008. Some hypothesized reasons for these changes include the spike in corn prices or economic conditions have influenced grading behavior.

To investigate the impact of the financial crisis and the increase of corn prices more clearly, we compared the estimated intervals before and during the financial crisis. Table 7 and Figure 9 show that the estimated interval for yield grade 1 became significantly narrower. In case of the non-parametric method, the estimated interval for yield grade 1 is getting narrower while intervals for other yield grade are similar before and during the financial crisis. This outcome might be the evidence to show the impact of macroeconomic events and increase of corn price on grading behavior in cattle market.

Seasonal Analysis

The primary factors in determining yield grade are weight and fatness (Field 2007). If cattle do not have higher feed quality and intake when they are exposed to cold or heat stress, they lose body weight (fat). Graders may have a prior belief that slaughter cattle processed in winter or summer may have less fat and weight than they do in other seasons with less environmental stress. This prior belief may lead to grading errors. Graders, thus, may call lower yield grades than actual yield grades indicate in winter and summer.

The results of the non-parametric method in Figure 11 and Table 8 report that estimated intervals are consistent across seasons. The results imply that heat and cold stress expectations on the part of graders do not influence grading behavior. The results could be explained in several ways: (1) there could be appropriate techniques to control extreme climate conditions, (2) during the sample periods, there were no extreme climate conditions, or (3) the graders do a good job of evaluating carcasses across seasons.

Weekly Analysis

The results in Figure 12 and Table 9 illustrate that the interval for yield grade 1 on Saturday is the widest among other weekdays. Further, the estimated interval on Monday is closer to the USDA standard than on other weekdays. This implies that USDA graders are more accurately grading on Monday than other weekdays. The estimated results indicate that grading outcomes are consistent with USDA graders more strictly grading beef carcasses at the beginning of the week.

Premium/Discount Analysis

From the previous section, support was found for the existence of grader bias in the beef yield grading system. Grader bias, or mistakes in grading, should result financial impacts on cattle feeders and packers over the study period. The data from the packing plants includes "measured" yield grade, "called" yield grades, the date of slaughter, and total weight for each carcass. Weekly weighted average premiums and discounts are reported by USDA. Through combining two data sets, financial gains/losses by producers and packers can be estimated under the grid-pricing mechanism if yield grades had been graded by the camera-grading system instead of human graders during our sample period. The financial gains/losses that producers could have earned or lost is meaningful because USDA is planning to reduce the number of human graders through utilizing the camera-grading system.

Table 10 reports the difference between "measured" and "called" yield grade's premiums/discounts $0.40 per cwt. The price difference means that producers could have lost $0.40 per hundredweight if yield grades would have been measured by camera-grading system during our sample period. It might be difficult to predict the financial impact of reducing human graders only using this analysis. The outcome, however, in this section gives us some clue about the future with the policy change.

Conclusion

The beef grading system is a major agricultural marketing system in the beef industry. USDA grades are a recognized world standard in beef quality. Yield grade is an important component of the grading system. While quality grade helps communication between producers (or packers) and consumers with respect to beef quality, yield grade makes communication easier between livestock producers and packers. The integrity of yield grade, however, can be guaranteed when grading is reliable. Thus, in this article, we examined the existence and possible sources of grader bias using the non-parametric estimation method that allows us to relax the normal distribution assumption. Through simulation exercises, we confirmed that our method perform well when the distribution of the sample is not normal. Our results suggested that economic factors and graders' mood are attributable to grading behavior.

Simulation studies found that non-parametric methods are useful in estimating the multiple cutoff points. Existing studies also showed parametric methods will lead to inconsistent estimated if the distribution of the sample does not follow a normal distribution. Since our sample is not distributed normally, a non-parametric method was adopted in the analysis.

Interval estimation analyses across time exhibited the possible sources of grader bias. First, annual analysis suggested that the financial crisis and the increase of feeding cost could influence grading behavior. It is interesting because the analysis showed that economic factors could be attributable to grading behavior. The cognitive bias in psychology can explain how economic factors affect grading behavior. Graders' subjective perception of their economic environments create a pattern of deviation in their judgment. Second, weekly analysis suggested that there are also "weekend effect" in the beef grading. This result showed how graders' mood influence their grading behavior.

Premiums and discounts data of cattle market were used to measure the financial impact of adopting camera-grading system. The outcome suggests that producers will incur financial loses on their cattle transactions if human graders will been replaced by cameras.

The analyses in this article supported the hypothesis of the existence of grader bias. Given this finding, the effort of the USDA to enhance the consistency of beef grading across time and places is inevitable. Utilizing the camera grading system will help to get rid of graders' subjective determination because a machine is not affected by economic and psychological factors. As the premium/discount analysis stated, however, reducing the human graders could cause financial losses of livestock producers. If financial losses are significant, there is a possibility that livestock producers use other beef grading systems instead of the USDA beef grading system. In reality, however, human graders calibrate the cameras for grading, so it is also possible that the financial losses are not significant. At the end, it will be better to utilize the camera grading system unless livestock producers’ financial losses are significant.

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Tables

Table 1. The Simulation Result: Normal Distribution with Mean 1.5 and Standard Deviation 0.5

Parameter	n_k = 50 (k = 1, 2, 3, 4, 5)	n_k = 50 (k = 1, 2, 3, 4, 5)	n_k = 500 (k = 1, 2, 3, 4, 5)	n_k = 1,000 (k = 1, 2, 3, 4, 5)
$\hat{C}_1^{np}$	2.003 (2.386)	1.960 (1.638)	2.078 (0.737)	2.050 (0.540)
$\hat{C}_2^{np}$	2.890 (2.053)	3.022 (1.786)	3.008 (0.829)	2.965 (0.419)
$\hat{C}_3^{np}$	4.014 (2.199)	4.025 (1.680)	4.006 (0.798)	3.968 (0.729)
$\hat{C}_4^{np}$	5.102 (1.910)	4.872 (2.355)	5.076 (0.854)	4.994 (0.513)
Ln L	0.4	0.7	3.6	7.4

Table 2. The Simulation Result: Lognormal Distribution with Location 1.5 and Scale 0.5

Parameter	n_k = 50 (k = 1, 2, 3, 4, 5)	n_k = 100 (k = 1, 2, 3, 4, 5)	n_k = 500 (k = 1, 2, 3, 4, 5)	n_k = 1,000 (k = 1, 2, 3, 4, 5)
$\hat{C}_1^{np}$	1.913 (2.761)	1.997 (1.531)	1.931 (0.750)	1.907 (0.554)
$\hat{C}_2^{np}$	2.957 (2.217)	3.063 (1.647)	3.007 (0.765)	3.014 (0.540)
$\hat{C}_3^{np}$	3.906 (2.425)	4.071 (1.534)	3.972 (0.782)	3.954 (0.446)
$\hat{C}_4^{np}$	4.950 (2.574)	4.885 (1.501)	4.963 (0.687)	5.012 (0.440)
Ln L	0.4	0.7	3.7	7.5

Table 3. The Simulation Result: Normal Distribution with mean 2.0 and Standard Deviation 0.5

Parameter	n_k = 50 (k = 1, 2, 3, 4, 5)	n_k = 100 (k = 1, 2, 3, 4, 5)	n_k = 500 (k = 1, 2, 3, 4, 5)	n_k = 1,000 (k = 1, 2, 3, 4, 5)
$\hat{C}_1^{np}$	2.437 (2.086)	2.164 (1.342)	2.278 (0.984)	2.268 (0.474)
$\hat{C}_2^{np}$	2.993 (2.127)	2.962 (1.397)	3.053 (0.697)	2.992 (0.434)
$\hat{C}_3^{np}$	3.824 (2.161)	3.949 (1.701)	4.007 (0.680)	4.011 (0.486)
$\hat{C}_4^{np}$	4.979 (2.370)	4.875 (1.884)	5.016 (0.678)	4.947 (0.406)
Ln L	0.3	0.7	3.5	6.9

Table 4. The Simulation Result: Normal Distribution with mean 1.5 and Standard Deviation 1.0

Parameter	$n_k = 50$ (k = 1, 2, 3, 4, 5)	$n_k = 100$ (k = 1, 2, 3, 4, 5)	$n_k = 500$ (k = 1, 2, 3, 4, 5)	$n_k = 1{,}000$ (k = 1, 2, 3, 4, 5)
$\hat{C}_1^{np}$	1.789 (3.121)	1.918 (2.027)	1.852 (0.893)	1.854 (0.730)
$\hat{C}_2^{np}$	2.826 (2.185)	3.017 (1.330)	3.034 (0.657)	2.998 (0.567)
$\hat{C}_3^{np}$	4.045 (1.748)	4.031 (1.076)	4.009 (0.662)	3.974 (0.523)
$\hat{C}_4^{np}$	5.198 (2.945)	5.059 (1.310)	4.957 (0.700)	5.006 (0.569)
Ln L	0.4	0.7	3.6	7.1

Table 5. Estimates of Cutoff Values (C_k) and Standard Errors (σ_u, σ_v) (Whole Sample Analysis)

Parameter	Estimate	Std Err	t Value	Pr > |t|	ln L
$\hat{C}^{np}{}_1$	2.260	0.919	2.5	0.014	
$\hat{C}^{np}{}_2$	3.094	0.773	4.0	0.000	103.8
$\hat{C}^{np}{}_3$	3.863	0.686	5.6	0.000	
$\hat{C}^{np}{}_4$	4.693	0.741	6.3	0.000	

Table 6. Estimates of Cutoff Values (C_k) and Standard Errors (σ_u, σ_v) (Annual Analysis)

Parameter	2005	2006	2007	2008
$\hat{C}_1^{np}$	2.289 (1.286)	2.407 (0.780)	2.276 (0.773)	1.976 (0.737)
$\hat{C}_2^{np}$	3.130 (0.911)	3.162 (0.736)	3.079 (0.645)	2.839 (0.893)
$\hat{C}_3^{np}$	3.859 (0.692)	3.898 (0.693)	3.889 (0.592)	3.570 (0.794)
$\hat{C}_4^{np}$	4.518 (1.024)	4.720 (0.760)	4.767 (0.725)	4.586 (0.939)
ln L	2.407	58.752	29.364	12.952

Note: Standard errors in parentheses

Table 7. Estimates of Cutoff Values (C_k) and Standard Errors (σ_u, σ_v) (Before/During Financial Crisis)

	$\hat{C}_1^{np}$	$\hat{C}_2^{np}$	$\hat{C}_3^{np}$	$\hat{C}_4^{np}$	ln L
Before (May 2005 – Jul 2007)	2.307 (0.906)	3.122 (0.755)	3.887 (0.646)	4.079 (0.755)	91.8
During (Aug 2007 –Oct 2008)	2.034 (0.757)	2.898 (0.859)	3.641 (0.807)	4.625 (0.961)	13.9

Note: Standard errors in parentheses

Table 8. Estimates of Cutoff Values (C_k) and Standard Errors (σ_u, σ_v) (Seasonal Analysis)

Parameter	Spring	Summer	Fall	Winter
$\hat{C}_1^{np}$	2.301 (0.853)	2.246 (0.944)	2.214 (1.258)	2.214 (1.258)
$\hat{C}_2^{np}$	3.118 (0.748)	3.078 (0.759)	3.112 (0.927)	3.112 (0.927)
$\hat{C}_3^{np}$	3.863 (0.632)	3.863 (0.781)	3.833 (0.698)	3.833 (0.698)
$\hat{C}_4^{np}$	4.701 (0.702)	4.719 (0.884)	4.574 (0.937)	4.574 (0.937)
ln L	52.932	40.784	5.559	8.972

Note: Standard errors in parentheses

Table 9. Estimates of Cutoff Values (C_k) and Standard Errors (σ_u, σ_v) (Weekly Analysis)

Parameter	Mon	Tue	Wed	Thu	Fri	Sat
$\hat{C}_1^{np}$	2.242 (0.753)	2.302 (1.073)	2.315 (1.232)	2.169 (0.675)	2.250 (1.252)	2.399 (0.685)
$\hat{C}_2^{np}$	3.083 (0.652)	3.088 (0.888)	3.128 (0.909)	2.981 (0.703)	3.099 (0.835)	3.196 (0.650)
$\hat{C}_3^{np}$	3.879 (0.540)	3.866 (0.713)	3.893 (0.599)	3.774 (0.743)	3.810 (0.762)	4.001 (0.694)
$\hat{C}_4^{np}$	4.984 (1.084)	4.636 (0.875)	4.830 (1.337)	4.659 (0.830)	4.670 (0.789)	4.718 (0.688)
Ln L	3.936	4.919	16.412	13.079	49.665	25.192

Note: Standard errors in parentheses

Table 10. Premiums/Discounts of "Measured" and "Called" Yield Grade (YG)

		Premiums/Discounts				Difference (A-B)	
		Measured YG (A)		Called YG(B)			
Year	"Called" YG	Sum	Average	Sum	Average	Sum	Average
2005	YG1	364	0.8	1,487	3.1	-1,123	-2.4
	YG2	592	0.3	3,495	1.5	-2,903	-1.3
	YG3	-1,980	-0.9	-616	-0.3	-1,365	-0.6
	YG4	-1,381	-5.7	-3,320	-13.7	1,939	8.0
	YG5	-112	-16.0	-140	-20.0	28	4.0
	Total	-2,517	-0.5	906	0.2	-3,423	-0.6
2006	YG1	320	1.4	723	3.2	-403	-1.8
	YG2	1,663	0.7	3,916	1.5	-2,253	-0.9
	YG3	-6,551	-1.4	-1,247	-0.3	-5,304	-1.1
	YG4	-8,877	-7.7	-13,830	-11.9	4,954	4.3
	YG5	-610	-10.7	-998	-17.5	388	6.8
	Total	-14,055	-1.6	-11,436	-1.3	-2,618	-0.3
2007	YG1	648	2.5	863	3.3	-215	-0.8
	YG2	2,290	1.1	3,295	1.5	-1,005	-0.5
	YG3	-4,780	-1.4	-715	-0.2	-4,064	-1.2
	YG4	-4,742	-9.8	-5,636	-11.7	894	1.9
	YG5	-423	-15.7	-498	-18.4	75	2.8
	Total	-7,007	-1.1	-2,691	-0.4	-4,316	0.7
2008	YG1	334	2.6	369	2.9	-35	-0.3
	YG2	1,455	1.5	1,525	1.6	-70	-0.1
	YG3	-103	-0.1	-433	-0.2	331	0.2
	YG4	-1,051	-5.1	-2,240	-10.9	1,189	5.8
	YG5	-100	-9.1	-202	-18.3	101	9.2
	Total	535	-0.2	-981	-0.3	1,516	0.5
Total	YG1	1,666	1.5	3,442	3.2	-1,775	-1.6
	YG2	6,001	0.8	12,231	1.5	-6,231	-0.8
	YG3	-13,413	-1.1	-3,011	-0.2	-10,402	-0.8
	YG4	-16,051	-7.7	-25,026	-12.0	8,976	4.3
	YG5	-1,246	-12.2	-1,838	-18.0	592	5.8
	Total	-23,044	-1.0	-14,202	-0.6	-8,841	-0.4

Note: All the values are reported in dollars per hundredweight ($/cwt).

Figures

Figure 1. Average Corn Price Received by Farmers, May 2005 - October 2008 (dollars per bushel)

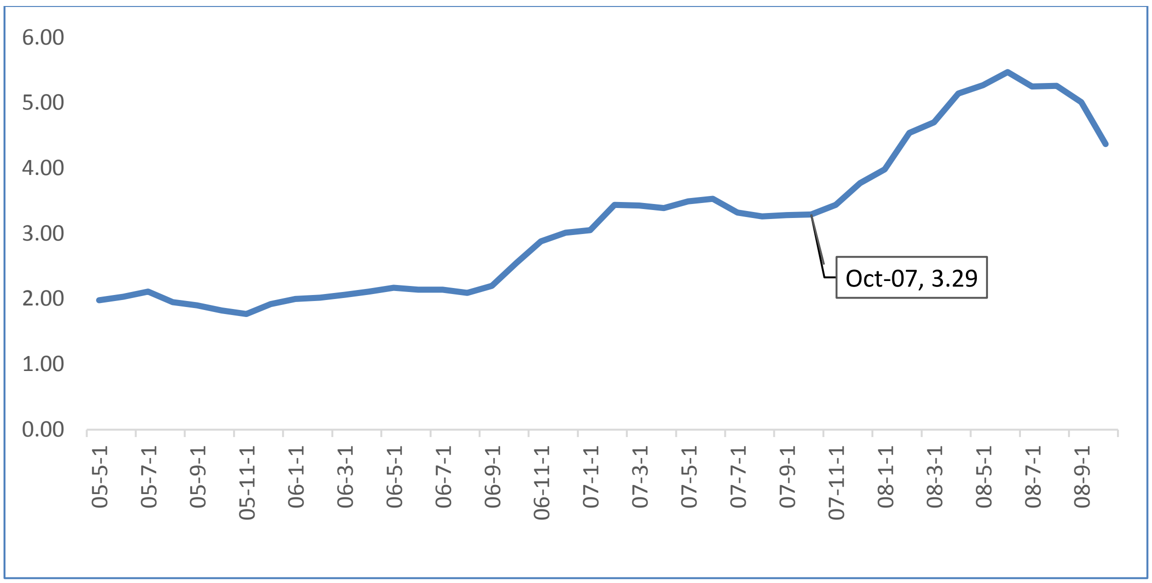
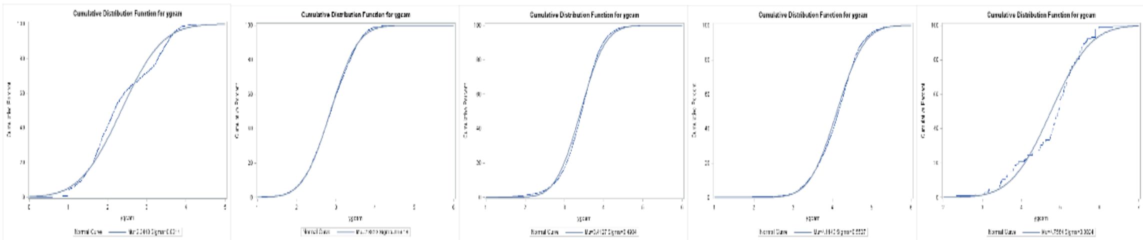
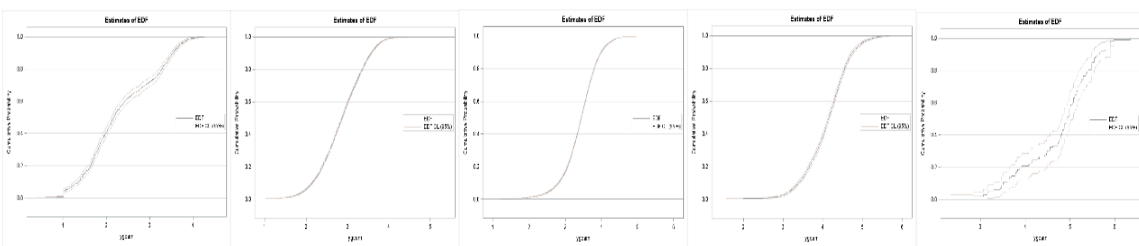


Figure 2. The Cumulative Density Functions of “Measured” Yield Grade Given “Called” Yield Grade.



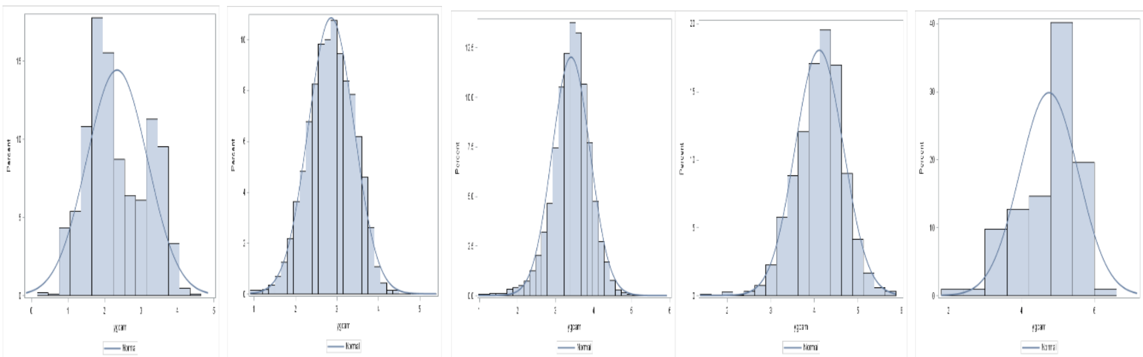
(Called yield grade = 1) (Called yield grade = 2) (Called yield grade = 3) (Called yield grade = 4) (Called yield grade = 5)

Figure 3. The Estimated Empirical Density Functions of “Measured” Yield Grade Given “Called” Yield Grade.



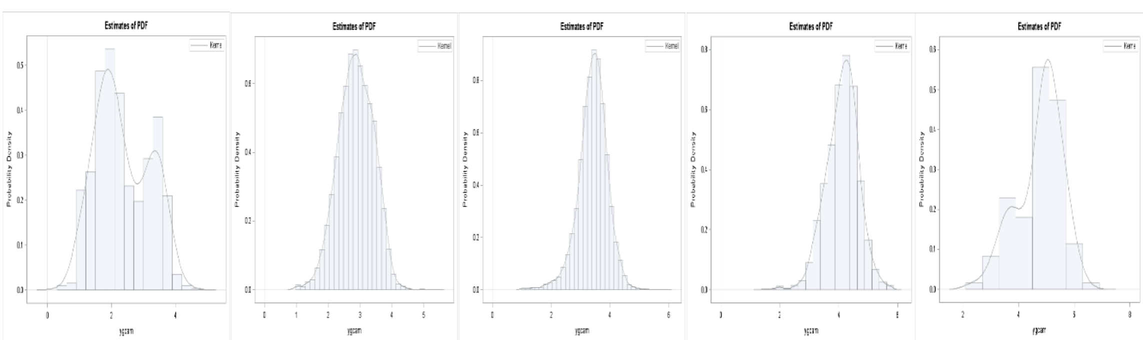
(Called yield grade = 1) (Called yield grade = 2) (Called yield grade = 3) (Called yield grade = 4) (Called yield grade = 5)

Figure 4. Probability Distribution Function (Normal Distribution) of "Measured" Yield Grade Given "Called" Yield Grade



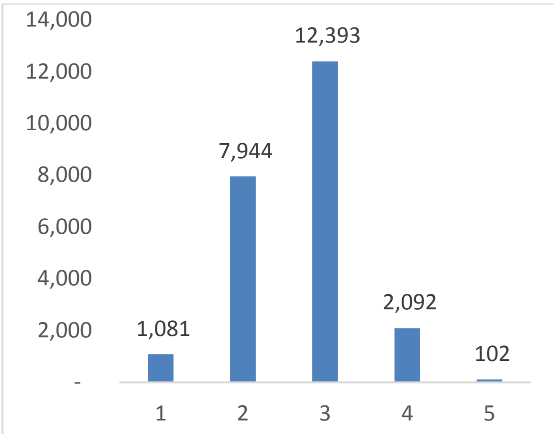
(Called yield grade = 1) (Called yield grade = 2) (Called yield grade = 3) (Called yield grade = 4) (Called yield grade = 5)

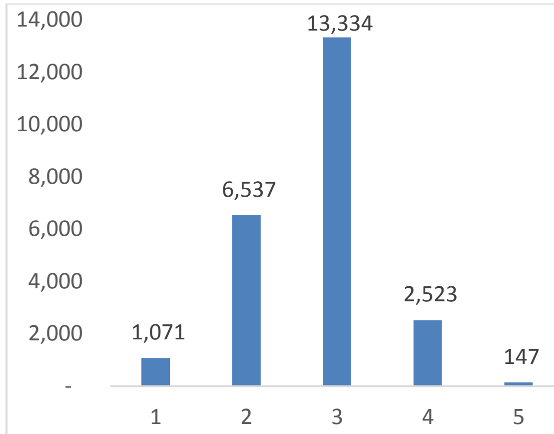
Figure 5. Kernel Functions of "Measured" Yield Grade Given "Called" Yield Grade



(Called yield grade = 1) (Called yield grade = 2) (Called yield grade = 3) (Called yield grade = 4) (Called yield grade = 5)

Figure 6. The Distribution of "Measured" and "Called" Yield Grade





(Measured Yield Grade) **(Called Yield Grade)**

Figure 7. Estimated and USDA Standard Intervals: Whole Sample Analysis

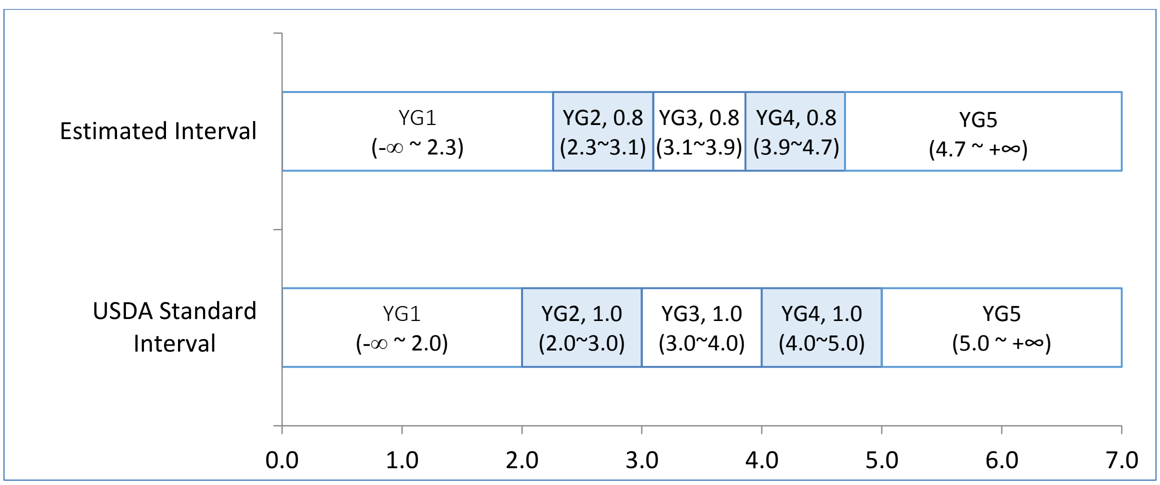


Figure 8. Estimated and USDA Standard Intervals: Annual Analysis

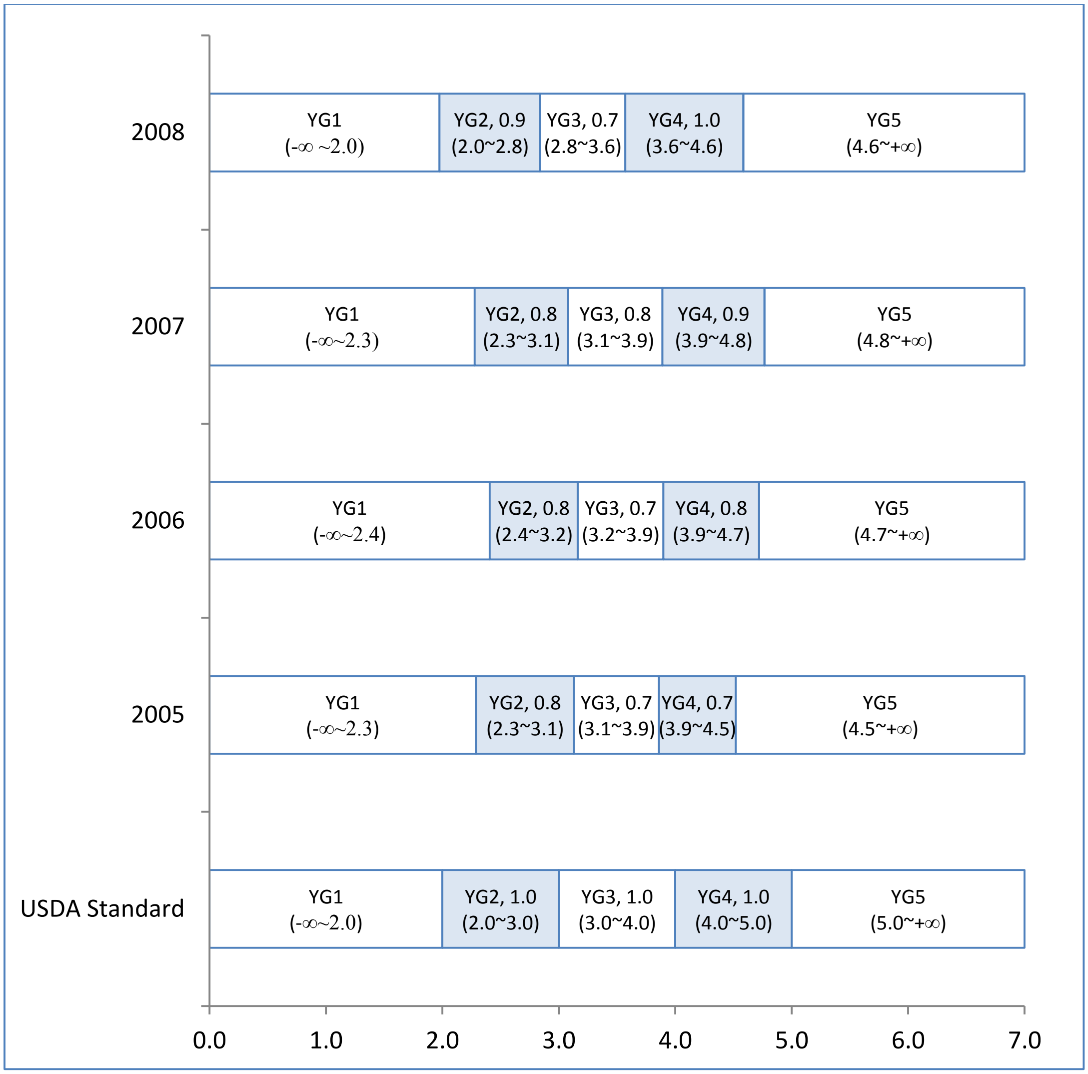


Figure 9. Estimated and USDA Standard Intervals: Before/During Financial Crisis

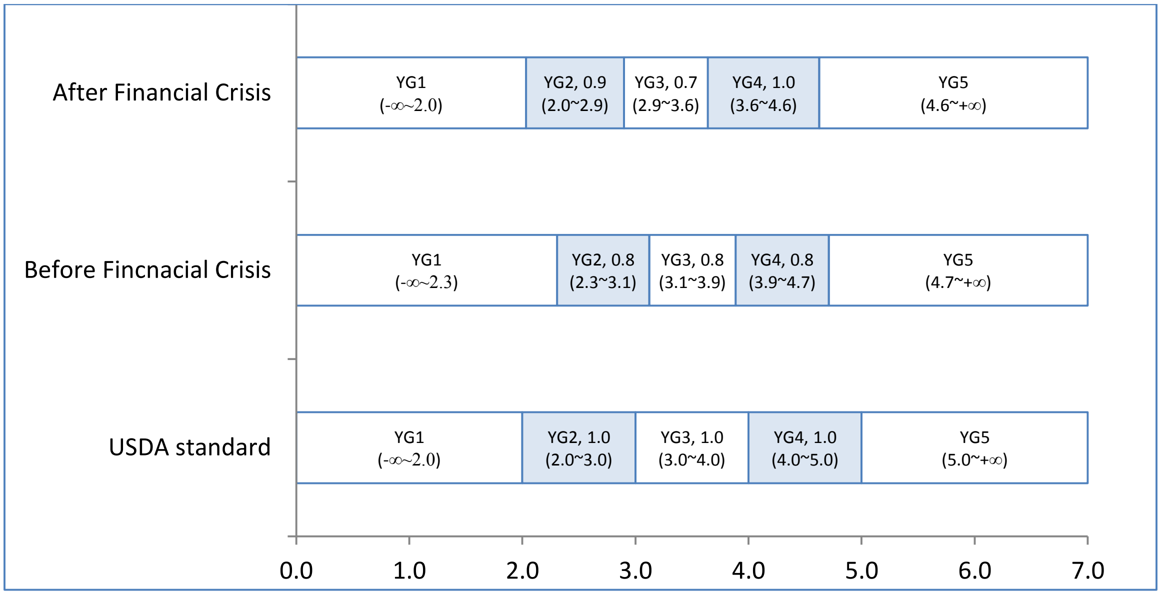


Figure 10. Monthly Average Retail Beef Price, 2000-2013 (cents per pound)

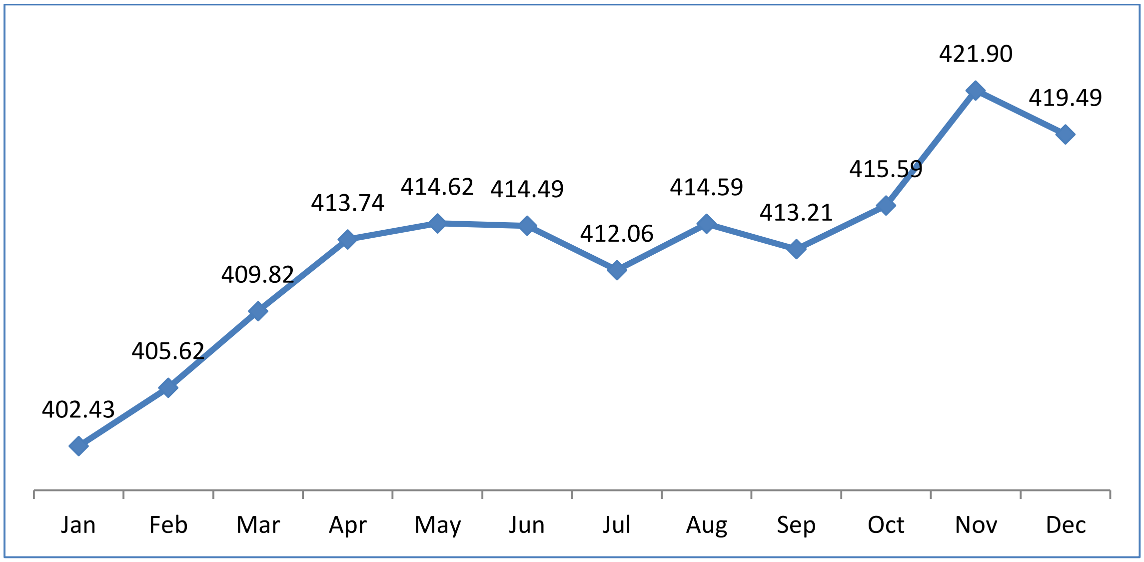


Figure 11. Estimated and USDA Standard Intervals: Seasonal Analysis

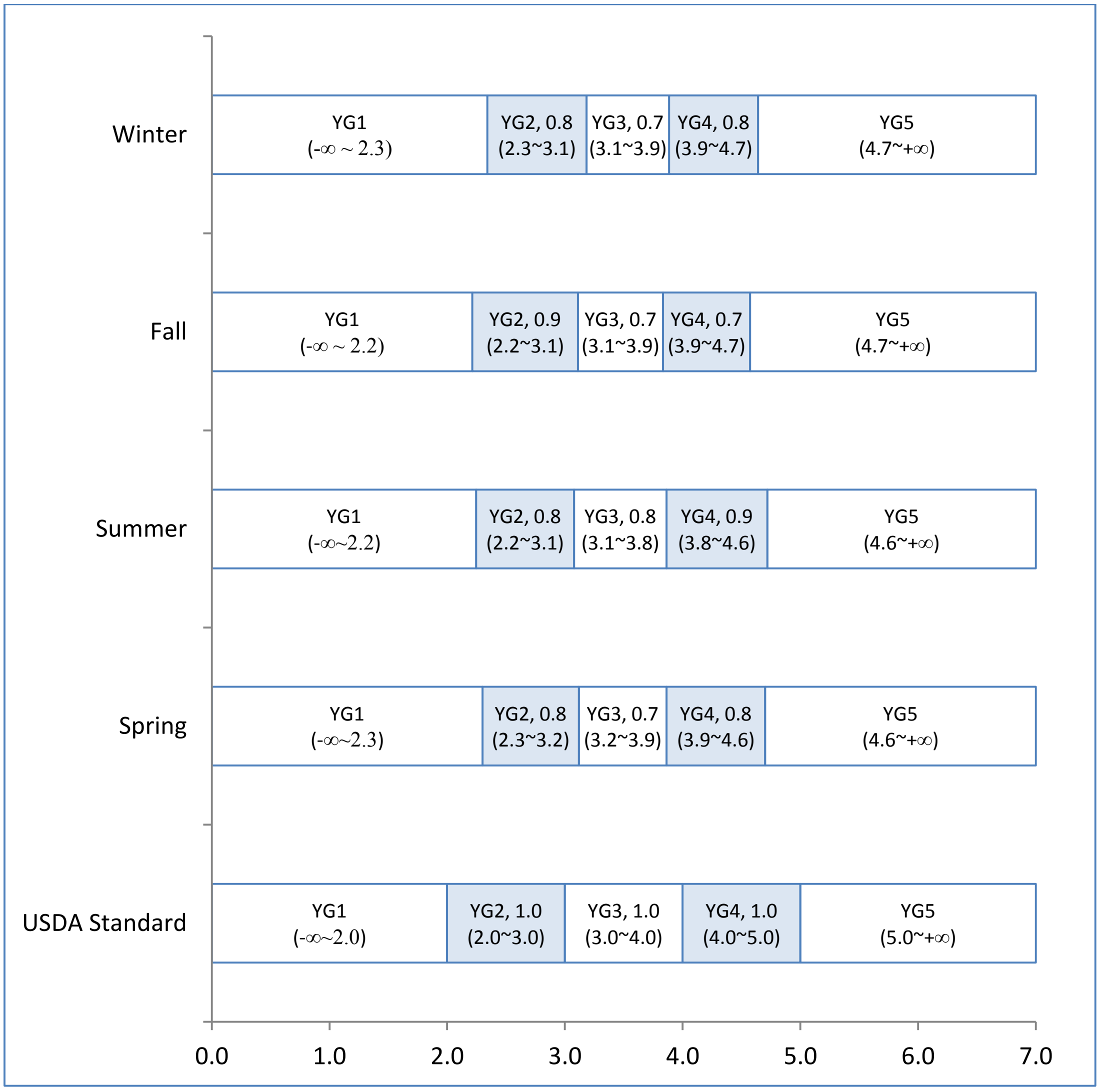


Figure 12. Estimated and USDA Standard Intervals: Weekly Analysis