# REFINING THE U.S. PEANUT GRADING SYSTEM

By

EDGAR F. PEBE DIAZ

Bachelor of Science
Universidad Nacional Mayor de San Marcos
Lima, Peru
1985

Master of Science
Oklahoma State University
Stillwater, Oklahoma
1996

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**Thesis Approved:**

Wade Brorsen

Thesis Advisor

Phil Kenkel

Kim B. Anderson

Kevin M. Currier

Wayne B. Powell

Dean of the Graduate College

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# CHAPTER ONE

# INTRODUCTION

### *Overview of the Problem*

The United States produced 1.6 million tons of peanuts, the production value of which was 1 billion dollars in 1998 (USDA, 1999). This represented almost 6% of world peanut production. Figure 1.1 shows that China, the world's largest peanut producer, India and Indonesia produced 35.5%, 29.5%, and 3.7% of the world peanut production in 1998, respectively.

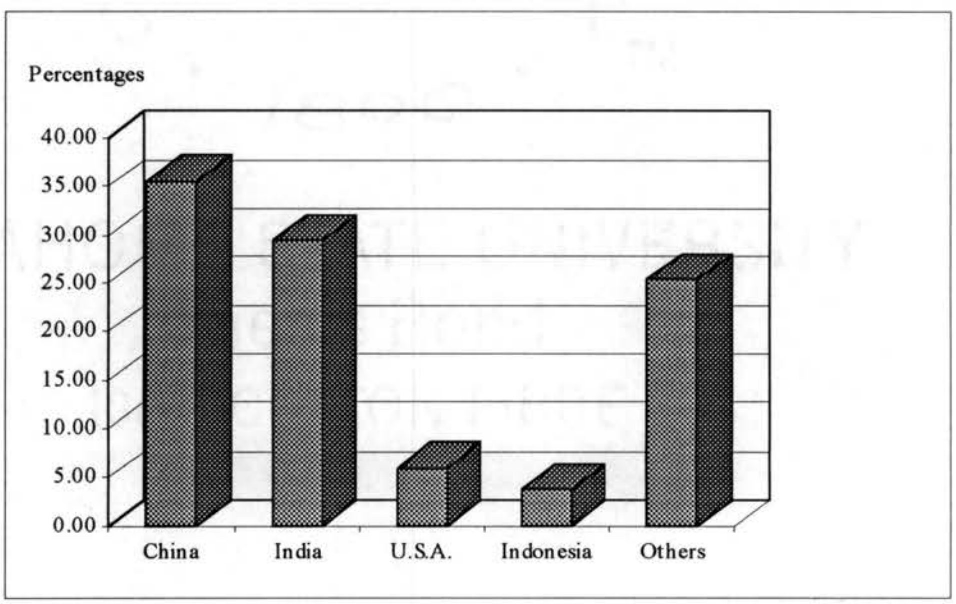


**Figure 1.1. Peanuts produced in the world's leading peanut producing countries, 1998**

Peanuts are grown in Georgia, Alabama, Florida, Virginia, North Carolina, Oklahoma, Texas, and New Mexico. Figure 1.2 shows that Georgia and Texas have by far the largest producing areas of peanuts, with 40% and 23% of the U.S. total production, respectively. The United States produces four peanut market types, namely virginia, runner, spanish, and valencia. However, runner peanuts account for 80% of the shelled peanuts used by the U.S. peanut industry.

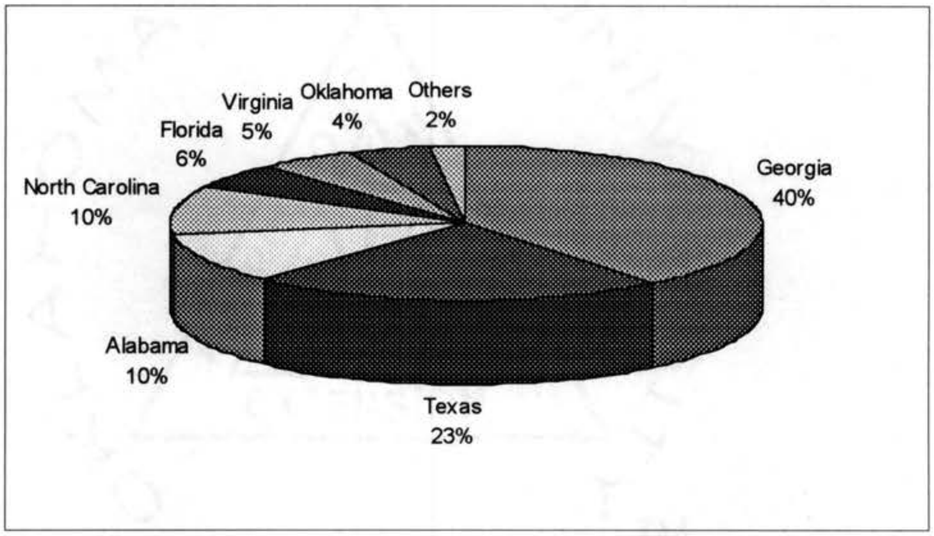


**Figure 1.2. Percentage of U.S. peanut production by state in 1998**

Under the Federal Support Program, quota peanuts, which are those peanuts grown within the farm poundage area, are used domestically. Nonquota or contracted peanuts, which are those peanuts grown in excess of the quota, have to be exported or used as a nonfood product. Quota peanuts are marketed subject to minimum grade standards, marketing controls, and support prices (Brooks; Crowder et al.; USDA, 1991).

The U.S. peanut industry competes for global markets with countries that can produce high quality peanuts at a low cost. For example, Argentina is displacing the

United States in the European market. A major concern to the U.S. peanut industry is increasing raw peanut imports from different countries, including Mexico under NAFTA. Valentine suggests that the United States must find ways for all the segments of the peanut industry to become more competitive in the world market. Even more, since the early 1990's the U.S. peanut industry has faced a dramatic decline in sales and consumption. This is the result of declining demand for peanuts and peanut products and increasing imports over the 1991-96 period. Also, the effects of recent adverse publicity about peanut allergies, misinformation about peanuts and their nutritional value, and decreased purchases by government breakfast programs have affected the U.S. peanut industry as a whole (Peanut News).

Florkowski reports that the National Peanut Council of America (NPCA), which includes farmer, sheller, manufacturer, and regulatory representatives, has been interested in improving peanut quality through the task force "U.S. Peanut Quality: An Industry Commitment." In this connection, we consider that efforts are also to be oriented to the refinement of the U.S. peanut grading system to reduce costs by reducing risk and signaling more accurate quality/price relationships to all segments of the peanut industry. Refining the U.S. peanut grading system is to be considered as a significant factor, but not the only one, to accomplish this goal. Since quality is the main variable affecting the price, grades must accurately reflect the true quality and value of U.S. peanuts marketed. That is, accurate pricing of peanuts depends on accurate grading.

The U.S. peanut grading system has changed little since the 1960s. The system was designed to keep the mathematics simple at a time when computers and calculators were bulky and expensive. There is a potential to refine the peanut grading system to provide better information to all the segments of the U.S. peanut industry. Due to randomness in the present grading system, incentives are not as clear to producers willing to make extra efforts for producing and delivering what buyers and consumers want; that is, good quality peanuts. Prices provide incentives to producers to grow and harvest their peanuts so that they have the desired characteristics. The concern of buyers is that they are paying for more peanuts than they receive. These problems affecting the U.S. peanut industry are worthy of study and policies to alleviate them may be adopted at a low cost.

### *Possible Problems with the U.S. Peanut Grading System*

Since peanuts needed by the industry come in various qualities, the U.S. peanut grading system is used to determine the quality and value of peanuts. Under the U.S. peanut grading system, all loads of farmers' stock and shelled stock peanuts are officially inspected and graded by the U.S. Department of Agriculture Federal/State Inspection Service (FSIS). "Farmers' stock" peanuts are those that have not been shelled. The loads are brought by the producers or sellers to the buying points or grading stations where the loads are graded by official or peanut contract graders (see chapter 2 for more details on the official grader). The FSIS employs about 2,000 graders at about 500 buying points across the producing areas to grade peanuts during harvest from August to November (Dowell, Meyer, and Konstance, 1994a).

Although automated grading systems have been designed to avoid subjectivity since the early 1990's and new computer developments for more accurate and consistent peanut grading and pricing are now available (Dowell, 1993; Dowell, Meyer, and Konstance, 1994b; Dowell and Powell; Powell, Sheppard, and Dowell; and, Lamb, Davidson, and Singletary), most grading is still done manually and visually. Hence, subjectivity and measurement errors in grading are still unavoidable.

Measurement errors in grading are mainly due to sampling, digital equipment, and human errors. Dowell, Meyer, and Konstance (1994a) point out that errors in peanut grading can cause (i) over- or underpayment to the seller or producer, (ii) improper segregation of the peanut load, or (iii) inaccurate grade information supplied to the buyer. Dowell (1992), and Whitaker found that the largest component of total error is improper sampling that in turn leads to misestimation of foreign material (FM). The research by Penny et al., cited by Dowell (1992), showed that human and equipment errors should not be ignored. Powell, Sheppard, and Dowell report that human errors basically include errors in recording weights, calculating percentages, and transcribing the results. Dowell (1992) reports that small errors in measuring grade factors can result in substantial differences in the price per ton or the dollar value of the load.

However, little attention has been paid to two possible problems with the U.S. peanut grading system. One problem is that some graders have been observed starting with cleaned samples of peanuts slightly greater than the prescribed 500g, presumably to reduce chances of regrading (Anderson). Due to time constraints and pressure during rush hours of the grading season, graders may use an overweight cleaned sample to ensure the allowable tolerance is met if some of the cleaned sample weight is lost (Dowell, Meyer, and Konstance [1994a]). For example, if a 500g cleaned sample is required, graders may begin with a 501g sample. Cleaned sample weights greater than 500g result in more peanuts in the sample. With overweight cleaned samples, graders tend to overestimate the grade factors measured and thus assign peanuts a higher price than is merited. Regardless of the actual cleaned sample weight, graders calculate the percentages of associated grade factors measured (grade percentages) as if the cleaned sample weight were exactly 500g as required by the U.S. peanut grading system. We will show that this practice introduces bias in peanut pricing. Several questions arise in connection with this first problem. Even if the cleaned sample weight is greater than the prescribed 500g (or 1,000g, for larger truckloads) does it make much difference? Why would a grader not start with a cleaned sample of exactly 500g? What are the grader's motivations to do so? If there is a problem, how extensive is it?

A second problem is related to some policies of the U.S. peanut grading system itself that indeed may be sources of randomness affecting the precision and accuracy of grade factors and prices. In our work with graders they have argued that taking an overweight cleaned sample does not matter because of the use of rounding of grade percentages, also known as pointing off. That is, graders are required to round the grade percentages to the nearest whole number, as prescribed by the U.S. peanut grading system (USDA, 1996). While taking overweight cleaned samples may not matter on an individual load, it does on average.

Table 1.1 shows an example of the effects of the use of rounding of grade percentages on peanut prices. Grade factors such as the percentages of sound mature kernels (SMK), sound splits (SS), other kernels (OK), total damage (TD), and hulls are calculated from a cleaned sample of 501.6g, with and without rounding. Note that, as mentioned above, under the current U.S. peanut grading system, grade percentages are calculated as if the cleaned sample weight were exactly 500g and rounded to the nearest whole number. This method of measuring grade factors will be referred to from now on as rounding/500g cleaned sample. We introduce three similar additional methods of measuring grade factors for comparison purposes: no rounding/500g cleaned sample, rounding/actual cleaned sample, and no rounding/actual cleaned sample.

**Table 1.1. An Example of Peanut Pricing**

| Grade Factors | Weight in Grams | Percentages Based on 500g Cleaned Sample: Rounding [1] | Percentages Based on 500g Cleaned Sample: No Rounding [2] | Percentages Based on Actual Cleaned Sample: Rounding [3] | Percentages Based on Actual Cleaned Sample: No Rounding [4] |
|---|---|---|---|---|---|
| Cleaned Sample | 501.6 | | | | |
| Total Kernels Riding the Screen(TKS) | 314.7 | | | | |
| Damaged Kernels (DK) | 1.3 | | | | |
| Sound Mature Kernels (SMK) | 313.4 | 63 | 62.68 | 62 | 62.48 |
| Sound Splits (SS) | 18.1 | 4 | 3.62 | 4 | 3.61 |
| Total Sound Mature Kernels (TSMK) | 331.5 | 67 | 66.30 | 66 | 66.09 |
| Other Kernels (OK) | 38.2 | 8 | 7.64 | 8 | 7.62 |
| Damaged Splits (DS) | 0.3 | | | | |
| Total Damage (TD) | 1.6 | 0 | 0.32 | 0 | 0.32 |
| Total Kernels (TK) | 371.3 | 75 | 74.26 | 74 | 74.03 |
| Hulls | 127.4 | 25 | 25.48 | 25 | 25.40 |
| Total Kernels and Hulls | 498.7 | 100 | 99.74 | 99 | 99.43 |
| Weight Discrepancy | 2.9 | 1 | 0.58 | 1 | 0.57 |
| Price per Ton in Dollars | | 586.13 | 579.62 | 577.55 | 577.77 |
| Price per Pound in Cents | | 26.61 | 26.31 | 26.22 | 26.23 |

Note: For illustration purposes, cleaned sample and weight discrepancy have been added to the information appearing on the FV-95 inspection certificate (USDA, 1996). Weight discrepancy is cleaned sample weight minus total kernels and hulls or the total weight of graded material. In this example, the price per ton in dollars is the price of TSMK ($8.581 per percent per ton) times the percentage of TSMK plus the price of OK ($1.4 per percent per ton) times the percentage of OK minus a financial penalty for SS over 4 percent ($0.8 per percent per ton). Total damage (TD) is damaged kernels (DK) plus damaged splits (DS). Although not explicitly done here, the dollar value of the load excluding loose shelled kernels (LSK) is price per ton times the net weight of the load (gross weight minus foreign material and excess moisture).

[1] This is the pricing method used under the current U.S. peanut grading system; that is, grade factors or characteristics are calculated as if the cleaned sample weight were exactly 500g and rounded to the nearest whole number (rounding/500g cleaned sample).

[2, 3, 4] These columns have been added to show how sensitive prices are to grade factors based on no rounding/500g cleaned sample, rounding/actual cleaned sample and no rounding/actual cleaned sample.

There is a $6.51 difference due to rounding between the prices per ton paid for the same truckload based on rounding/500g cleaned sample and no rounding/500g cleaned sample. Note also that there is almost no differences due to rounding between the prices per ton based on rounding/actual cleaned sample and no rounding/actual cleaned sample.

Rounding is now unnecessary since calculators are readily available and all grade data are entered on computers. Buyers do not like rounding because it makes the measurement of grade factors less accurate. Graders do not like rounding because it can cause the percentages to add up to less than 99 percent or more than 101 percent even when the graders make no errors. The size of the errors created by the use of rounding and how often rounding causes the need to regrade are not available in any published literature.

Therefore, there is a need to document the effects of overweight cleaned samples and the use of rounding of grade percentages so that, for example, formal training programs for peanut graders can show the need for starting with a cleaned sample weight as close to 500g as possible and/or the possibility of get rid of rounding.

### *Rationale and Significance*

Overweight cleaned samples and the use of rounding of grade percentages may currently be affecting the precision and accuracy of peanut grade factors and prices. These two problems may increase the risk faced by the buyer and add noise to the market signal received by the seller or producer and thus hurt the ability of the U.S. peanut grading system to signal quality/price relationships (Schaffner, Schroder, and Earle). If there is some evidence that these problems really exist in the U.S. peanut industry, then policies should be implemented to correct these problems.

Previous research on the relationship between grade and sample size has only looked at the effects of grade requirements such as whether a 100, 500 or 1000g sample should be used (Penny et al.; Dickens and Whitaker; Whitaker; Whitaker, Dickens and Giesbretch). In the early 1950's, Penny et al., cited by Dowell (1992), showed that the variability between samples was reduced as sample size increased. However, the actual increase in accuracy was not as large as theoretical predictions. One of the main reasons was that errors associated with visually assessing damage in the large samples were found. Although a reduction in variability was associated with increased sample size, little quantitative data was reported and the grading procedures were somewhat different than those being used currently.

Total variability $V_t$ reported by previous researchers is defined in terms of sampling variance $V_s$ and measurement variance $V_m$, and thus $V_t = V_s + V_m$. Dowell (1992) points out that $V_s$ occurs since it is not practical to grade the entire truckload and a sample must be obtained and graded. Also, $V_m$ occurs when the grader or equipment measures grade factors. Thus, reducing $V_s$ or $V_m$ will reduce the total variability.

Taylor argues that increasing the sample size will reduce $V_s$ by a proportional amount, assuming the quality factors are uniformly distributed throughout the truckload. However, increasing sample size should reduce $V_s$, but $V_m$ may increase due to the larger sample that must be handled and graded. Thus, if sample size is increased, $V_t$ will increase in proportion to the change in $V_s$ and $V_m$. Then, $V_m$ can be reduced by eliminating or reducing grader subjectivity and equipment variability.

We do not mean to say that sampling variation is not important. Based on this literature and our conversations with peanut buyers and graders, we would expect that improper sampling is a large source of error. However, sampling mainly affects estimates of foreign material (FM). Foreign material is not used for calculating the price per ton, but its estimate greatly affects the dollar value of the load, since foreign material is subtracted from the gross weight of the truckload. The instructions to graders about sampling are carefully designed. Sampling biases occur when graders do not follow instructions. Sampling is important since the heavier material tends to settle in the center of the truckload. Monitoring of sampling would likely be costly. Hence, the focus of this study is instead on policy changes aiming to reduce $V_m$ that, in turn, could increase the precision and accuracy of the grade factors and prices at relatively low cost.

Previous research consistently shows that increasing sample size is one component of total error that can affect all grade factors (Dowell, 1992; Whitaker et al. 1992, 1994; Tsai et al.; Davidson et al.). However, none of this literature has considered the bias created by taking overweight cleaned samples and then measuring grade factors as if the cleaned sample weight were exactly 500g. Also, none of this literature has investigated the use of rounding of grade percentages as a source of error.

These two possible problems will also have repercussions at the industry level as a whole. Peanuts previously and officially graded at the buying point are sampled and graded again at the processing plant by company graders, also known as private graders. Some buyers argue that, on average, grade factors measured by official graders and those measured by private graders differ significantly. Generally, buyers must absorb any extra payment due to overpricing. However, buyers could recoup this loss by either paying less for nonquota peanuts or charging a higher margin. Because of overweight cleaned samples and because of the use of rounding, noise is introduced and thus peanut markets are less efficient. This noise in grading and then pricing peanuts might cause buyers to charge a quality risk premium.

Brorsen, Grant, and Rister found that rice graders in various locations in Texas also used different cleaned sample weights. This made it difficult for them to compare discounts and premiums across locations. Thus, the findings here may apply to more commodities than just peanuts. Also, marketing margins have consistently been shown to be sensitive to changes in risk (Brorsen et al.; Holt). Reducing risk should reduce marketing margins. Because a minimum price is established for quota peanuts, all of the risk premium may appear as high margins for nonquota peanuts whenever quota peanuts are priced at the minimum. Thus, any risk created by peanut grading will introduce noise to the market signal and reduce the ability of the U.S. peanut grading system to clearly signal quality/price relationships.

To our knowledge, the effects of overweight cleaned samples and the size of the errors introduced by the use of rounding of grade percentages have received no research attention. Also, the motivations or incentives for the graders to take overweight cleaned samples are poorly understood. We will argue that rounding creates an incentive for graders to take overweight cleaned samples. We propose to look at ways the U.S. peanut grading system could be refined. The implications of this study may be useful for government policy, when revising the "Farmers' Stock Peanuts Inspection Instructions Handbook" by the U.S. Department of Agriculture FSIS, and for formal training programs for peanut graders.

### *General Objective*

The general objective of this study is to improve the precision and accuracy of grade factors and prices obtained with the U.S. peanut grading system.

### *Specific Objectives*

The specific objectives are to

1. Explain the motivations or incentives that could lead graders to take overweight cleaned samples.
2. Determine the theoretical form of an optimal training-auditing policy for the USDA within a moral hazard framework assuming monitoring is costly.
3. Estimate the effects of overweight cleaned samples on the price per ton paid to producers.
4. Estimate the effects of overweight cleaned samples and the weight discrepancy on grade factors measured.
5. Estimate the variability of prices introduced by the use of rounding of grade percentages.
6. Estimate the probability of regrading.
7. Estimate the differences between average grade factors and prices measured by official and private graders in an actual situation.

*Procedures*

This study has two parts. The first part entitled theoretical framework is an attempt to accomplish objectives 1 and 2. The theoretical framework is used to explain the graders' motivations to take overweight cleaned samples (objective 1) and to model the moral hazard problem existing in peanut grading. The proposed model allows introducing nonmonetary incentives such as a measure of pricing accuracy in the USDA's objective function and the subjective or psychic income from internal and/or external sanctions in the grader's utility function. The model is used to help understand USDA's policy choices (objective 2). The combining of both economic and sociological incentives represents a considerable advancement over previous moral hazard models. The USDA may find it more economical to influence graders' behavior by creating cognitive dissonance through training and rules rather than by using economic incentives.

The second part deals with formally testing the set of hypotheses related to objectives 3 through 7. Because of the lack of data on both overweight cleaned samples and the weight discrepancy in grams, there was a need to develop a designed experiment that generated data for objectives 3 through 6. The repeated-measures experimental design and fixed and random effects models are used to test the effects of overweight cleaned samples on the price per ton paid to producers (objective 3). Also, fixed and random effects models are used to test the effects of overweight cleaned samples and the weight discrepancy on grade factors (objective 4). The paired-differences experimental design is used to test the effects of the use of rounding of grade percentages on the variability of prices (objective 5). Nonparametric and parametric methods are used to estimate the probability of regrading (objective 6). The nonparametric approach is based on the empirical p.d.f. method. Under the parametric approach, a new probability distribution, called a normal-jump distribution, is used to estimate the probability of regrading without rounding of grade percentages. This new probability distribution allows numerous small errors that are approximated with a normal distribution and infrequent large human errors. A multiple-dimension Monte Carlo integration is then used to estimate the probability of regrading with rounding of grade percentages.

With the data provided by a major U.S. peanut buyer, differences between average grade factors and prices measured by official and private graders are calculated to provide some evidence that official graders may take overweight cleaned samples (objective 7).

# CHAPTER II

## THEORETICAL FRAMEWORK

This chapter provides a theoretical framework to explain the graders' motivations or incentives to take overweight cleaned samples. In general, we argue that the graders' motivations may come from the desire to avoid regrading and the absence of effective norms and internal or external sanctions. We point out that formal training programs for peanut graders can help internalize the norms and create the internal and external sanctions. We also identify the conditions under which an optimal training-auditing policy implemented by the USDA, the principal, can efficiently induce the graders, the agent, to apply higher effort levels with less monitoring.

This chapter is divided into four parts. The first part presents the graders' motivations or incentives to take overweight cleaned samples as stated in objective 1. The second part explains the concepts taken from sociology that will be used in the proposed model. The third part introduces the moral hazard problem existing in peanut grading. The fourth part presents the proposed model that includes nonmonetary incentives such as pricing accuracy aimed by the USDA and the graders' subjective or psychic income from either internal or external sanctions. The model is adapted to help understand USDA's policy choices as stated in objective 2.

### *The Grader's Motivations to Take Overweight Cleaned Samples*

Although there are many perspectives on the motives for grading and related issues in the economic literature (see, for example, Hennessy), the motivations that could lead peanut graders to take overweight cleaned samples has not been researched. We will show in chapter 4 that the tendency to take cleaned sample weights greater than the prescribed 500g introduces bias and noise in peanut grading and pricing. That is, this action leads to giving peanuts a higher grade and price than merited. If the buyer fails to perceive the bias, this action may favor the seller at the buyer's expense. But, who is the grader? What is (are) the motivation(s) or incentive(s) behind the grader taking overweight cleaned samples? Is the current U.S. peanut grading system itself the source of the incentives?

The official grader, also known as the peanut contract grader, from now on he or she will be referred to as the grader, is an independent contractor who has properly executed and accepted a short-term independent contractor agreement, completed training, and been issued a federal license to grade peanuts (Oklahoma FSIS). According to the U.S. peanut grading system, the measurement of the grade factors or characteristics begins with a cleaned sample weight of 500g or not larger than 500.5g for truckloads of 10 tons or less. Note that for truckloads over 10 tons, a cleaned sample of 1,000g is used instead. The set of grade factors $G$ measured with the cleaned sample weight $S$, and primarily used to calculate the price per ton $P$, are the percentages of sound mature kernels (SMK), sound splits (SS), and other kernels (OK). We provide additional information on the grading and pricing procedures in chapter 3.

During grading it is extremely difficult for the grader to be more accurate than 0.1g since even a little breeze can cause the digital scale reading to fluctuate. The grader takes some time to get a weight within 0.1 of 500g since a single peanut pod weighs between 0.7 and 1.2g. If the desired weight is not achieved, the grader is supposed to remove a small handful of peanut pods and then drop them back on one at a time until the desired weight is achieved. This must be done to avoid any bias that could be created if a big pod were removed and a little one added in order to achieve the desired weight. Hence, one motivation or incentive for the grader to take overweight cleaned samples could simply be to avoid taking the time to get the cleaned sample weight precise.

However, under the U.S. peanut grading system, the cleaned sample weight is not recorded on the FV-95 inspection certificate. Thus, there is no way to observe that the grader has taken an overweight cleaned sample. Otherwise, the cleaned sample weight differential $\Delta S$, defined as $\Delta S = S - 500$, could be thought of as a perfect statistical signal of the grader's effort level $e$ applied to get the weight precise.

Also, measuring grade factors involves randomness. Some cleaned sample weight is lost during the grade analysis. This is mostly dust (dirt) that is created when peanuts are shelled. The maximum amount of cleaned sample weight that can be lost without regrading, known as the allowable tolerance $T$, is 1 percent of the cleaned sample weight; that is, $0 \le T \le 5g$. However, regardless of his or her grading abilities, the grader usually ends up having some cleaned sample weight loss after grading. This weight loss will be referred from now on to as the weight discrepancy $W$ and defined as the difference between the cleaned sample weight $S$ in grams and the weight of total kernels and hulls in grams $K$, or the total weight of graded material. That is

**(2.1)** $$W = S - K \text{ or } K = S - W .$$

To check the accuracy of the grade factors measured, the grader adds up the percentages of total kernels and hulls. The U.S. peanut grading system stipulates that if the final sum of total kernels and hulls $K$ falls outside of the 99-101% (or 495-505g) range, peanuts must be regraded. That is, regrading $R$ is required if the final sum of total kernels and hulls is less than 99 percent or greater than 101 percent. Regrading is a function of the cleaned sample weight $S$ and the weight discrepancy $W$ is defined by

**(2.2)**
$$R(S,W)=\begin{cases}0 \text{ if } 495 \le S-W \le 505 \\ \\ 1 \text{ if } S-W < 495 \text{ or } S-W > 505.\end{cases}$$

The weight discrepancy $W$ found after grading comes from (i) the weight of the cleaned sample lost as dust and kernels during the analysis, (ii) infrequent equipment and human errors, and (iii) the policy itself of dividing the grade percentages by 500g as if the cleaned sample weight were exactly 500g, and rounding the grade percentages to the nearest whole number.

The weight lost is mostly dust or dirt created when the cleaned sample is shelled. Small pods or kernels can fall through the sheller grate or get stuck in the grading screen. Under pressure, a careless grader may forget to clean the pan containing kernels from a previous analysis or might accidentally drop some kernels into the pan when grading. These kernels will show up in the next grade analysis and thus affect the accuracy of the grade factors being then measured. Hence, the grader can even end up having an amount of total kernels and hulls $K$ in grams greater than the cleaned sample weight $S$. Equipment errors generally occur when the divider or the digital scale is not properly adjusted. As mentioned in the introduction, human or mental errors include errors in recording weights, calculating the percentages, and transcribing the results. Usually the grader does not lose pods and kernels or make errors, but when the grader does so, these errors may be large.

Therefore, values of the weight discrepancy $W$ greater than the allowable tolerance $T$ or negative values of the weight discrepancy indicate that the grader has made a large error when grading. The weight discrepancy $W$ will then allow capturing large errors made by the grader. Hence, the probability distribution of the weight discrepancy $W$ in grams can be used to estimate the probability of regrading as explained in chapter 3.

A second motivation is that the grader would also like to take overweight cleaned samples to reduce the chances of regrading. Recall that the trailer cannot be dumped until grading is completed. During the peak of the grading season, the grader is pressured to complete his or her work quickly, so the grader may be tempted to avoid regrading. During slack times, regrading is just additional work that could have been avoided. Since the grader is paid by the hour, the grader might seem to have no monetary incentives to avoid regrading during working hours, but could have a monetary incentive to desire regrading during overtime. Note that the grader is paid 1.5 times his or her wage when grading or regrading are done during overtime. Also, rounding that may cause regrading may be partly to blame for the incentive to take overweight cleaned samples.

If these motivations are true, then what factors explain this behavior or attitude? In the absence of more specific information on the grader's personal, economic and psychological characteristics, we must assume certain behavior patterns. For example, in terms of Maslow's hierarchical ranking of needs, cited by Howard, Brinkman, and

Lambert, the grader may be more motivated by satisfaction in what he or she does than by security and status/power. That is, the grader may be more concerned with his or her higher-order "satisfaction needs", rather than his or her lower-order "security needs". We can assume that the grader could be more motivated by the subjective or psychic income $I$ due to the satisfaction from or pride in what he or she does for society. Also, the grader could be more motivated by the subjective appraisal of rewards (prizes, recognition, praise, etc) he or she receives from doing a good job. Note that if the grader, for example, is more concerned with a lower-order "security need", this may result in a fear of failure that induces him or her to reduce the chances of regrading, but could lead to more formal monitoring.

According to the neoclassical theory, the grader wants to maximize his or her utility function $U$. If rational, the grader could be more motivated by increased wage income $Y$, and more hours of leisure $H$. Recall that the grader is hired for a short period of time, generally four months, under the conditions stipulated in a standard contract shown in Appendix A.

The grader's wage income $Y$ from this seasonal job comes from working 8 hours at a fixed hourly wage rate $\omega$ that, based on the grader's years of experience, ranges from 6.10 to 7.50 dollars. Also, the grader receives 1.5 times and 2 times the fixed hourly wage rate for services provided outside of working hours and during holidays, respectively. For this reason, the grader may be motivated to work overtime and have less hours of leisure. However, there is no evidence that the grader will want to regrade more often during working hours.

As shown in Appendix A, the grader is reimbursed an additional hourly fee of 1.50 dollars for those periods working as a lead grader, and a daily inconvenience differential based on the one-way distance in miles of the assigned grading station from the grader's residence. An additional payment of 2.00 dollars per day is added to the inconvenience differential if there are no commercial dining facilities available within a radius of 5 miles of the assigned grading station. The grader may claim transportation reimbursement at the rate of 28 cents per mile when the grader has accepted assignment to a grading station that requires use of the grader's own vehicle. No lodging costs are paid to the grader.

In addition to the wage income $Y$ and leisure $H$, we hypothesize that certain nonmonetary or subjective incentives may also influence the grader's utility. For example, under the assumption that there exists an internal sanctioning system, as defined below, the grader should feel internal punishments when taking overweight cleaned samples. In this connection, Coleman points out that internal sanctions $\Phi$ coming from feeling bad for doing a bad job may affect the grader's utility. Also, factors such as inexperience or unskilledness, laziness, laxness, sickness, poor working conditions, stress, pressure felt from, conflicts with or criticisms made by other members of the grading team, and complaints made by the seller or the buyer about the accuracy of the grade factors measured, may influence the grader's utility. Indeed, these factors influence the grader's disutility $D$ from grading. External sanctions or rewards $\Psi$ for doing a good job such as prizes and awards that lead to prestige, reputation or recognition, personal satisfaction or expectations of long term employment with the USDA, also really matter. Hence, it is reasonable to assume that internal and/or external sanctions influence the grader's utility and have to be considered in analyzing the grader's motivations.

Therefore, one step toward understanding the grader's motivations is to determine what income (psychic or monetary, or both) are relevant from the grader's perspective. Psychic income could be more prevalent among seasonal, fixed-wage people such as the grader (Jose and Crumly, cited by Howard, Brinkman, and Lambert). Thus, variables influencing psychic and/or wage income are important in designing any motivation strategy. Also, these variables could help determine the incentives that, in turn, will induce the grader to apply higher effort levels with less monitoring.

The above arguments suggest that the grader maximizes a hybrid utility function that combines wage income $Y$, leisure $H$, subjective or psychic income $I$ from internal or external sanctions, and effort $e$. This utility function is given by

**(2.3)** Utility = U(wage income, leisure, psychic income from internal or external sanctions, effort).

Here, the use of subjective or psychic income allows the inclusion of social sanctions in the analysis. Crowley also applied the social sanctions approach in a model used to explain decisions of people taking part in funding commodity promotion and research programs.

We explain next the sociological concepts such as social norms, and internal and external sanctions that are related to the subjective or psychic income concept to be used in the proposed model.

### *Social Norms and Internal and External Sanctions*

Coleman points out that tools such as social norms and internal and external sanctions could be useful to explain micro-level social problems. From this perspective, the concept of a norm is important to explain first how societies or groups of people function.

According to Coleman, social norms "… specify what actions are regarded by a set of persons as proper or correct, or improper or incorrect. They are purposively generated, in that those persons who initiate or help maintain a norm see themselves as benefiting from its being observed or harmed by its being violated. Norms are ordinarily enforced by sanctions, which are either rewards for carrying out those actions regarded as correct or punishments for carrying out those actions regarded as incorrect. Those holding a norm, claim a right to apply sanctions and recognize the right of others holding the norm to do so." (Coleman, pp. 242-43).

We can assume that the norm in peanut grading is to closely follow the instructions appearing on the Inspection Instructions Handbook so that grade factors and prices are measured precisely. The proper or correct action is to begin the grade analysis with a cleaned sample weight as close to 500g as possible. The USDA, on behalf of the interests of the U.S. peanut industry, is liable for maintaining the norm. If the grader's action is subject to the norm, the grader will take into account the norm. Even more, the grader will also consider the accompanying potential rewards or punishments.

However, Coleman points out that these potential rewards or punishments are not absolute determinants of his or her actions, but elements that might influence his or her decisions about what actions to carry out in his or her own interest. There must be a consensus in the sense that the right to control the action must be held by others, not by the grader. That is, others have the authority over the action. For example, others mean a set of actors including the other members of the grading team, the Federal/State area supervisor, the buyer or the seller, the producer or the consumer. An effective norm will come into existence when others have the right to affect the direction that the grader's action will take. Some theoretical tasks arise in this connection.

First, the internalization of the norm has to take place. In other words, the grader has to internalize the norm. If the norm has been internalized, the grader will feel internally generated rewards for taking a 500g cleaned sample or feel internally generated punishments for doing the opposite.

Second, the grader's action generates positive and negative externalities for all segments of the U.S. peanut industry, especially for the buyer and the seller. That is, the action of taking overweight cleaned samples may benefit the seller but hurt the buyer, or vice versa. Hence, this may result in potential conflicts of interests since the action has positive externalities for the seller and negative externalities for the buyer. This is a problem that at least the USDA and the grader must be aware of.

Third, the externalities will create a demand for effective norms. The demand will arise from the potential beneficiary of the norm. For example, if the buyer (seller) feels he has the right to have at least partial control over the action, or exert the right to apply sanctions on the grader, this may be done at the buyer's (seller's) expense.

Fourth, the application of sanctions may entail costs for the USDA. In the grader's case there are several kinds of sanctions ranging from those damaging or enhancing his or her prestige or reputation to those providing economic benefits. These sanctions will directly affect the grader's utility. For example, when the USDA gives the grader a verbal reprimand if observed taking overweight cleaned samples, the USDA is using an internal sanction that assumes the existence of an internal sanctioning system. So, the USDA is trying to strengthen that system. An external sanction occurs when the USDA praises the grader's action or gives the grader a prize or award to reward the proper action.

Fifth, as a result of all these factors, the USDA's goal may be to get the grader to identify with the USDA's interest. The identification in the grader will generate the internal sanctions for future actions. Hence, direct strategies such as formal training programs (workshops, seminars, conferences) are important means for creating consciousness and internalizing the norm in the grader. Here, the objective is to reinforce directly the belief that certain actions are right and others are wrong.

Let's go back to the analysis of the grader's motivations. We have assumed that the grader gets utility from wage income, leisure, subjective or psychic income from internal and/or external sanctions, and effort, as given by equation (2.3).

We assume next that the USDA decides to implement a strategy based on training, auditing, and incentives deriving from internal and/or external sanctions to induce the grader to apply his or her higher effort levels. This strategy is presented next under a moral hazard setting.

### *Moral Hazard in Peanut Grading*

Standard agency theory deals with asymmetries of information that develop after the signing of a contract. There are two types of informational problems that arise in these settings: those resulting from hidden actions and those resulting from hidden information (Mas-Colell, Whinston, and Green). An example of the hidden action case, also known as moral hazard[1], is illustrated by the USDA's inability to know the real capabilities of the grader or to observe how much effort the grader applies when grading. That is, the grader's effort levels are not observable. Hence, the USDA has an informational disadvantage. This problem is referred to as nonobservability in contract theory (Strausz). The hidden information case arises when the grader often ends up having better information than the USDA about the technicalities of the grading process that could be used to improve the U.S. peanut grading system.

We assume that the main problem existing in the U.S. peanut grading industry is a hidden action or moral hazard problem in which there is an incentive problem between the USDA, the principal, and the grader, the agent. The grader is assumed to control an action that is normally interpreted as his or her effort level $e$. The USDA temporarily hires the grader to perform grading services and receives the output generated by the grader's actions: an accurate price $P$.

We define the price $P$ as a function of the set of grade factors $G$ that, in turn, are a function of the cleaned sample weight $S$ and the weight discrepancy $W$, conditional on the training $t$ received by the grader and his or her effort level applied $e$. That is,

**(2.4)** Price = P[G(Cleaned Sample, Weight Discrepancy; Training, Effort)].

The USDA will then follow an auditing policy of the grader's performance by using some measure of pricing accuracy.

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[1] Mas-Colell, Whinston, and Green point out that the literature's use of the term moral hazard is not entirely uniform. See footnote on p. 477 of Mas-Colell, Whinston, and Green. Also, for earlier moral hazard models, see, cited by Strausz, Holmstrom (1979); Shavell; Mirrless; and Grossman and Hart. For more information on recent developments in moral hazard models, see Prescott.

Following Strausz, the incentive problem is depicted as follows: the grader dislikes to perform effort $e$, but the USDA wants him or her to apply higher effort level as it tends to improve the accuracy of the grade factors $G$ and thus the price $P$. Therefore, the grader and the USDA's preference related to the action are opposed. Moreover, the grader's action is currently noncontractible. In general, current grading contracts do not specify, for example, that the grader has to begin the grade analysis with a cleaned sample weight as close to 500g as possible. So, the USDA and the grader can only contract on general grading services as currently being done. Hence, the price $P$, the output, is assumed to correlate imperfectly with the grader's action. Strausz states that "imperfect correlation implies that output is partly random and partly affected by the agent's action" (Strausz, p. 8). If the grader's action were contractible and clearly specified in the contract, the USDA and the grader would be able to write contingent contracts on it. For example, if the contract clearly stipulates that the grader must take a 500g cleaned sample to begin the grade analysis, then the USDA would be able to influence the grader's actions. However, there is no guarantee to observe that the grader will finally take a 500g cleaned sample, even in the presence of contingent contracts. Therefore, a demand for monitoring arises.

Under the USDA operational structure, the Federal/State area supervisor is responsible for monitoring the grader's actions in his or her assigned grading station or territory. However, it is extremely difficult and costly to monitor and supervise every single grading operation in a timely manner. When the lead grader or the supervisor is present, the grader may follow the standard operating procedures for peanut grading, but not at other times. That is, trying to observe the grader taking overweight cleaned samples is likely to be unsuccessful because of the "halo effect." The grader would likely take cleaned sample weights closer to 500g if the grader knew he or she was being watched. Thus, monitoring of the grader's actions under the current USDA operational structure would be costly and probably inefficient. Peanuts are currently saved from every truckload, but the grader's performance is rarely audited or evaluated.

The monitoring problem in agencies has been previously addressed in the literature. Previous research on monitoring (investigation) policies, cited by Dye, include Townsend; Evans; Baiman and Demski; Kanodia; and Lambert. In this study, we use the term "auditing" instead of "investigation". This is because the investigation or more precisely the auditing takes place after the agent has finished the action and the agent's output is publicly observed, but not while the agent was doing the action that would imply "monitoring". Also, we use the term "statistical signal" instead of "monitor" of the agent's effort level. The term "monitor" would connote the person or the party responsible for monitoring the grader's actions.

The model presented below is based on a standard hidden action or moral hazard model (Varian; Mas-Colell, Whinston, and Green). However, past moral hazard models has rarely considered nonmonetary incentives as explained below. The proposed model provides insights into better understanding policies that could lead to higher pricing accuracy with less monitoring.

### *The Model*

We consider the case in which the USDA, acting on behalf of the U.S. peanut industry, attempts to attain a high level of pricing accuracy at a grading station. We suppose the nonmonetary output (incentive) is defined by a certain measure of pricing accuracy obtained by the grader during the grading season. This measure of pricing accuracy $\Delta$, conditional on the effort applied by the grader, can be given by the average absolute pricing error

**(2.5)** $$\Delta = \frac{1}{n}\sum_{i=1}^{n}\left|P_i - \bar{P}_i\right| \quad \text{for } i = 1, \ldots, n,$$

where $P_i$ is the *ith* observed price based on grade factors measured from the work sample, $\bar{P}_i$ is the corresponding *ith* true price or expected price based on grade factors measured as if the entire truckload were shelled, and $n$ is the number of lots graded during the grading season.

For simplicity, we assume the grader can only take one of two effort levels $e \in \{e_L, e_H\}$, that measure how hard the grader works when grading, where $e_L$ is the low effort level and $e_H$ is the high effort level, with $e_H > e_L$. Note that the USDA will follow a strategy to induce the grader to take the high effort level $e_H$ since this leads to lower expected pricing errors, but entails a greater difficulty for the grader.

We also suppose the USDA implements a training program previous to the grading season to improve the grader's grading skills and thus pricing accuracy. The density and distribution functions of the pricing error depend upon training $t$ and effort levels $e$ and thus are represented as $f(\Delta; t, e)$ and $F(\Delta; t, e)$, with $f(\Delta; t, e) > 0$ for all $e \in \{e_L, e_H\}$ and all $\Delta \in [0, a]$. Training should reduce expected pricing errors and thus we assume $\partial F(\Delta; t, e) / \partial t < 0$. Also, expected pricing errors should be less with high effort and so $F(\Delta; t, e_L) < F(\Delta; t, e_H)$.

We assume the USDA is risk neutral and thus its goal is to minimize the expected average absolute pricing error given by

$$\int_{0}^{a} \Delta f(\Delta; t, e_H) d\Delta \tag{2.6}$$

subject to its operating budget $C^*$ and the constraints related to induce the grader to apply his or her high effort level $e_H$.

Also, we assume the USDA's operating cost function per grading season is continuous and is given in terms of four choice variables. First, the total wage $w$ paid to the grader in dollars during the grading season also assumes hours of labor are fixed. Second, since the pricing error is unobservable, the incentive payment $\chi$ in dollars is a function of certain values of an imperfect statistical signal $\theta$ of effort, with density given by $g(\theta; m, \Delta)$, with $g(\theta; m, \Delta) > 0$ for all $\Delta \in [0, a]$ and all $\theta \in [0, b]$. This implies that the incentive payment $\chi(\theta)$ to the grader is necessarily random.

The imperfect statistical signal $\theta$ of effort can be proxied by the average absolute "buying-point" pricing error derived from the difference between the *jth* price based on the grade factors measured from the work sample by the grader $P_j^G$ and the associated *jth* price based on the grade factors measured from the check sample by the supervisor $P_j^S$. That is,

$$\theta(m; \Delta) = \frac{1}{m} \sum_{j=1}^{m} \left| P_j^G - P_j^S \right|, \tag{2.7}$$

where $m$ is the number of auditing samples the supervisor takes and regrades in accordance with the USDA's auditing policy. Note that $\theta(m;\Delta)$ has measurement error and thus

$$(2.8) \qquad \left|P_j^G - P_j^S\right| = \left|P_j - \bar{P}_j\right| + \eta_j, \text{ for } j = 1,\ldots, m.$$

If $\eta_j \sim N(0,\gamma^2)$, then $E(\theta) = \Delta$ and the conditional variance is $\mathrm{Var}(\theta - \Delta) = \gamma^2 / m$. The number of auditing samples $m$ is small and auditing is usually done only at the start of the season or if there are complaints made by either buyers or sellers. The measurement error in the auditing policy is captured by $g(\theta; m, \Delta)$. This measurement error reduces the desirability of the incentive scheme by requiring more samples $m$ to get a given level of pricing accuracy (lower expected pricing errors).

Thus, the expected incentive payment is given by $\int_0^b \chi(\theta)g(\theta; m, \Delta)d\theta$. The function $\chi$ is non increasing in $\theta$, so $\chi(\theta_1) \le \chi(\theta_2)$ if $\theta_1 > \theta_2$. To make the problem tractable we assume that the function $\chi(\theta)$ depends on a single parameter $\alpha$ and that $\partial\chi(\theta;\alpha)/\partial\alpha > 0$. Therefore, the third choice variable is the single parameter $\alpha$.

The cost of auditing $c$ is given by the price of auditing one lot $r$ and the number of auditing samples $m$ taken under the auditing policy and thus $c = rm$. The fourth choice variable is the cost of the training program $t$ in dollars per grader incurred at the beginning of the grading season.

Then, the USDA's expected cost in dollars per grader per season is

$$(2.9) \qquad C^* = \int_0^a \left( w + rm + t + \int_0^b \chi(\theta,\alpha)g(\theta; m, \Delta)d\theta \right) f(\Delta; t, e_H)d\Delta.$$

If the USDA decides not to implement the incentive payment policy and not to audit, its cost is $(w+t)$. Although incentive payments are not currently paid, note that incentive payments are in the USDA's choice set. However, the USDA has other policy choices such as changing the rules (say, rounding). These could also change the incentives.

We assume that the grader is risk averse and wants to maximize a von Neumann-Morgenstern utility function $U(.)$ over his or her the total wage income $w$, the incentive payment $\chi(\theta,\alpha)$ received at the end of the season, and the monetarized value of the subjective or psychic income $I$ deriving from the observed values of the imperfect statistical signal $\theta$, and the training $t$ received. Also, we assume that the grader gets disutility $D$ from effort $e$, with $D(e_H) > D(e_L)$. We assume that $U(.)$ is strictly concave and twice continuously differentiable, with $U'(.) > 0$ and $U''(.) < 0$, and $D'(.) > 0$ and $D''(.) > 0$.

We suppose that one alternative to the risk-averse, effort-averse grader is to not accept the contract. If so, the grader gets utility $\bar{U}$. Hence, the grader has to receive at least his or her opportunity cost or reservation utility level $\bar{U}$ if the grader is supposed to participate or accept the contract that stipulates that the grader has to apply his or her high effort level $e_H$. Thus,

$$\textbf{(2.10)} \qquad \int_0^a\int_0^b U_H\left[w+\chi(\theta,\alpha)+I(\theta,t,e_H)\right]g(\theta;m,\Delta)d\theta\, f(\Delta;t,e_H)d\Delta - D(e_H) \geq \bar{U}.$$

This constraint is the participation or individual rationality constraint.

The grader will choose the high effort level $e_H$ if his or her expected utility from working hard $\int U_H(.)$ is greater or equal to the expected utility he or she gets from working less $\int U_L(.)$. That is,

$$\textbf{(2.11)}\quad \begin{aligned}&\int_0^a\int_0^b U_H\left[w+\chi(\theta,\alpha)+I(\theta,t,e_H)\right]g(\theta;m,\Delta)d\theta f(\Delta;t,e_H)d\Delta - D(e_H)\\ &\geq \int_0^a\int_0^b U_L\left[w+\chi(\theta,\alpha)+I(\theta,t,e_L)\right]g(\theta;m,\Delta)d\theta f(\Delta;t,e_L)d\Delta - D(e_L),\end{aligned}$$

otherwise the grader will choose the low effort level $e_L$. This is the incentive compatibility constraint. Figure 2.1 shows the timing of events for the USDA's optimal training-auditing policy scheme.

| t=0 | t=1 | t=2 | t=3 | t=4 | t=5 |
|---|---|---|---|---|---|
| USDA Provides Training to the Grader and Offers Contract that Stipulates Incentive Scheme and Effort level | Grader Performs Grade Analysis | Effort level Has been Applied that Influences Grade factors And prices | Prices Have been Calculated | USDA takes and Regrades certain Number of Check samples To observe Value of Imperfect Statistical Signal of Effort | Grader's Compensation Based on Values of Imperfect Statistical Signal observed by USDA |

**Figure 2.1 Time-line for the optimal training-auditing policy scheme**

Therefore, the USDA wants to minimize the expected pricing errors by following a training-auditing strategy that induces the grader to apply his or her high effort level $e_H$ subject to its expected cost (2.8) and the constraints (2.9) implying that the grader is given an expected utility level no less than his or her reservation utility level $\bar{U}$, and (2.10) deriving from its inability to observe the grader's effort levels. The solution to this optimization problem is to find an optimal policy scheme $(w, \alpha, m, t)$ that efficiently induces the grader to apply his or her high effort level $e_H$ in order to attain the lower expected pricing errors. That is, the minimum of the following program

**(P.1)**
$$\underset{w,\alpha,m,t}{\text{Min}} \int_0^a \Delta\, f(\Delta; t, e_H)\, d\Delta$$

subject to

$$C^* \geq \int_0^a \left( w + rm + t + \int_0^b \chi(\theta, \alpha) g(\theta; m, \Delta) d\theta \right) f(\Delta; t, e_H) d\Delta,$$

$$\int_0^a \int_0^b U_H \left[ w + \chi(\theta, \alpha) + I(\theta, t, e_H) \right] g(\theta; m, \Delta) d\theta\, f(\Delta; t, e_H) d\Delta - D(e_H) \geq \bar{U},$$

$$\int_0^a \int_0^b U_H \left[ w + \chi(\theta, \alpha) + I(\theta, t, e_H) \right] g(\theta; m, \Delta) d\theta\, f(\Delta; t, e_H) d\Delta - D(e_H)$$
$$\geq \int_0^a \int_0^b U_L \left[ w + \chi(\theta, \alpha) + I(\theta, t, e_L) \right] g(\theta; m, \Delta) d\theta\, f(\Delta; t, e_L) d\Delta - D(e_L),$$

$$w, \alpha, m, t \geq 0.$$

Note below that $U_H(.)$ and $U_L(.)$ are the grader's utility function when the grader chooses high effort level $e_H$ and low effort level $e_L$, respectively. The observation that some graders are applying low effort levels suggests that the USDA's current policy is not the solution to the optimality problem set up above. It could be that the USDA may not be willing to spend sufficient money to get the incentive compatibility constraint to hold.

The Lagrangian $L(w,\alpha,m,t)$ for the minimization of (P.1) is given by

$$\textbf{(2.12)}\quad L=\int_0^a \Delta\, f(\Delta;t,e)d\Delta+\phi\left[C^{*}-\int_0^a\left(w+rm+t+\int_0^b \chi(\theta,\alpha)g(\theta;m,\Delta)d\theta\right)f(\Delta;t,e_H)d\Delta\right]$$

$$+\lambda\left[\int_0^a\int_0^b U_H(.)g(\theta;m,\Delta)d\theta\, f(\Delta;t,e_H)d\Delta-D(e_H)-\bar{U}\right]$$

$$+\mu\left[\int_0^a\int_0^b U_H(.)g(\theta;m,\Delta)d\theta f(\Delta;t,e_H)d\Delta-D(e_H)-\int_0^a\int_0^b U_L(.)g(\theta;m,\Delta)d\theta f(\Delta;t,e_L)d\Delta+D(e_L)\right],$$

where $\phi,\lambda,\mu$ are the multipliers for constraints (2.8), (2.9) and (2.10), respectively. The multiplier $\phi$ measures the change in pricing accuracy with an additional dollar of expenditure. The multiplier $\lambda$ measures the change in pricing accuracy with a change in the grader's reservation utility. The multiplier $\mu$ measures the change in pricing accuracy with a change in the difference in expected utilities required to get the high effort level from the grader. Also, $w$, $\alpha$, $m$, and $t$ are all strictly positive. Note that all functions in (2.12) are continuous and thus Riemann-integrable. We assume that the functions have continuity at the upper limits $a$ and $b$ of integration.

The standard Kuhn-Tucker first-order conditions are obtained by differentiating (2.12) with respect to $w$, $\alpha$, $m$, and $t$, respectively. The first-order condition for wage payment comes from differentiating (2.12) with respect to $w$. So,

$$\textbf{(2.13)}\qquad \frac{\partial L}{\partial w}=-\phi\int_0^a f(\Delta;t,e_H)d\Delta+\lambda\left[\int_0^a\int_0^b U'_H(.)g(\theta;m,\Delta)d\theta\, f(\Delta;t,e_H)d\Delta\right]$$

$$+\mu\left[\int_0^a\int_0^b U'_H(.)g(\theta;m,\Delta)d\theta\, f(\Delta;t,e_H)d\Delta-\int_0^a\int_0^b U'_L(.)g(\theta;m,\Delta)d\theta\, f(\Delta;t,e_L)d\Delta\right]=0.$$

The integral in the first term is one so after rearranging terms, (2.13) becomes

$$-\phi+\lambda\int_0^a\int_0^b U'_H(.)g(\theta;m,\Delta)d\theta f(\Delta;t,e_H)d\Delta+\mu\int_0^a\int_0^b U'_H(.)g(\theta;m,\Delta)d\theta f(\Delta;t,e_H)d\Delta$$

$$-\mu\int_0^a\int_0^b U'_L(.)g(\theta;m,\Delta)d\theta f(\Delta;t,e_L)d\Delta=0,$$

or

$$-\phi+[\lambda+\mu]\int_0^a\int_0^b U'_H(.)g(\theta;m,\Delta)d\theta f(\Delta;t,e_H)d\Delta-\mu\int_0^a\int_0^b U'_L(.)g(\theta;m,\Delta)d\theta f(\Delta;t,e_L)d\Delta=0.$$

Dividing through by $\int_0^a\int_0^b U'_H(.)g(\theta;m,\Delta)d\theta f(\Delta;t,e_H)d\Delta$ and rearranging terms, we get

$$\frac{\phi}{\int_0^a\int_0^b U'_H(.)g(\theta;m,\Delta)d\theta f(\Delta;t,e_H)d\Delta}=[\lambda+\mu]-\mu\int_0^a\int_0^b U'_L(.)g(\theta;m,\Delta)d\theta f(\Delta;t,e_L)d\Delta.$$

Then, the first-order condition for wage payment $w$ is

**(2.14)**

$$\frac{1}{\int_0^a\int_0^b U'_H(.)g(\theta;m,\Delta)d\theta\, f(\Delta;t,e_H)d\Delta}=\frac{\lambda}{\phi}+\frac{\mu}{\phi}\left[1-\frac{\int_0^a\int_0^b U'_L(.)g(\theta;m,\Delta)d\theta\, f(\Delta;t,e_L)d\Delta}{\int_0^a\int_0^b U'_H(.)g(\theta;m,\Delta)d\theta\, f(\Delta;t,e_H)d\Delta}\right].$$

Note that the first-order condition for wage payment $w$ is a function of the ratio $\int_0^a\int_0^b U'_L(.)g(\theta;m,\Delta)d\theta f(\Delta;t,e_L)d\Delta/\int_0^a\int_0^b U'_H(.)g(\theta;m,\Delta)d\theta f(\Delta;t,e_H)d\Delta$. This fraction or marginal rate of substitution measures the ratio of the expected marginal utility the grader gets when working less to the expected marginal utility the grader gets when working more.

The implication of condition (2.14) is that the grader may get more expected marginal utility for pricing errors that are statistically more likely to occur under $e_H$ than under $e_L$ in the sense of having the ratio less than one. For this to hold, $I(\theta,t,e_L) < I(\theta,t,e_H)$ and $U_L\left[w+\chi(\theta,\alpha)+I(\theta,t,e_L)\right] < U_H\left[w+\chi(\theta,\alpha)+I(\theta,t,e_H)\right]$. This may suggest that the psychic income from an internal sanction or the satisfaction from doing a good job by exerting high effort levels after receiving training is an important means to increase both the grader's welfare and expected pricing accuracy.

Similarly, to derive the first-order condition for the incentive scheme $\chi(\theta,\alpha)$, we differentiate (2.12) with respect to $\alpha$. Then,

**(2.15)**

$$\frac{\partial L}{\partial \alpha} = -\phi\left[\int_0^a\int_0^b \chi_\alpha(\theta,\alpha)g(\theta;m,\Delta)d\theta\, f(\Delta;t,e_H)d\Delta\right] + \lambda\left[\int_0^a\int_0^b U'_H(.)\chi_\alpha(\theta,\alpha)g(\theta;m,\Delta)d\theta\, f(\Delta;t,e_H)d\Delta\right]$$

$$+\mu\left[\int_0^a\int_0^b U'_H(.)\chi_\alpha(\theta,\alpha)g(\theta;m,\Delta)d\theta\, f(\Delta;t,e_H)d\Delta - \int_0^a\int_0^b U'_L(.)\chi_\alpha(\theta,\alpha)g(\theta;m,\Delta)d\theta\, f(\Delta;t,e_L)d\Delta\right] = 0,$$

where $\chi_\alpha(\theta,\alpha) = \dfrac{\partial \chi(\theta,\alpha)}{\partial \alpha}$. Rearranging terms, (2.15) is given by

$$\phi\int_0^a\int_0^b \chi_\alpha(\theta,\alpha)g(\theta;m,\Delta)d\theta\, f(\Delta;t,e_H)d\Delta = [\lambda+\mu]\int_0^a\int_0^b U'_H(.)\chi_\alpha(\theta,\alpha)g(\theta;m,\Delta)d\theta\, f(\Delta;t,e_H)d\Delta$$

$$-\mu\int_0^a\int_0^b U'_L(.)\chi_\alpha(\theta,\alpha)g(\theta;m,\Delta)f(\Delta;t,e_L)d\Delta.$$

Dividing by $\int_0^a\int_0^b U'_H(.)\chi_\alpha(\theta,\alpha)g(\theta;m,\Delta)d\theta f(\Delta;t,e_H)$ and rearranging terms, it follows that

$$\frac{\phi\int_0^a\int_0^b \chi_\alpha(\theta,\alpha)g(\theta;m,\Delta)d\theta f(\Delta;t,e_H)d\Delta}{\int_0^a\int_0^b U'_H(.)\chi_\alpha(\theta,\alpha)g(\theta;m,\Delta)d\theta f(\Delta;t,e_H)d\Delta}=[\lambda+\mu]-\mu\frac{\int_0^a\int_0^b U'_L(.)\chi_\alpha(\theta,\alpha)g(\theta;m,\Delta)d\theta f(\Delta;t,e_L)d\Delta}{\int_0^a\int_0^b U'_H(.)\chi_\alpha(\theta,\alpha)g(\theta;m,\Delta)d\theta f(\Delta;t,e_H)d\Delta}.$$

Therefore, the first-order condition for the incentive scheme $\chi(\theta,\alpha)$ is

**(2.16)**

$$\frac{1}{\int_0^a\int_0^b U'_H(.)\chi_\alpha(\theta,\alpha)g(\theta;m,\Delta)d\theta f(\Delta;t,e_H)d\Delta}=\frac{\lambda}{\phi}\frac{1}{\int_0^a\int_0^b \chi_\alpha(\theta,\alpha)g(\theta;m,\Delta)d\theta f(\Delta;t,e_H)d\Delta}$$

$$+\frac{\mu}{\phi}\frac{1}{\int_0^a\int_0^b \chi_\alpha(\theta,\alpha)g(\theta;m,\Delta)d\theta f(\Delta;t,e_H)d\Delta}\left[1-\frac{\int_0^a\int_0^b U'_L(.)\chi_\alpha(\theta,\alpha)g(\theta;m,\Delta)d\theta f(\Delta;t,e_L)d\Delta}{\int_0^a\int_0^b U'_H(.)\chi_\alpha(\theta,\alpha)g(\theta;m,\Delta)d\theta f(\Delta;t,e_H)d\Delta}\right].$$

The current USDA policy has no formal incentive payments. If that is the case, then the USDA selects $\chi(\theta,\alpha)=0$. As condition (2.16) suggests, the marginal effect of the incentive payment, plus training and other nonmonetary incentives, may motivate the grader to apply his or her high effort level.

Analogously, the first-order condition for the number of auditing samples is derived from differentiating (2.12) with respect to $m$. Then,

**(2.17)**
$$\frac{\partial L}{\partial m}=-\phi\left[\int_0^a\int_0^b \chi(\theta,\alpha)g_m(\theta;m,\Delta)d\theta f(\Delta;t,e_H)d\Delta+r\right]$$

$$+\lambda\left[\int_0^a\int_0^b U_H(.)g_m(\theta;m,\Delta)d\theta f(\Delta;t,e_L)d\Delta\right]+\mu\left[\int_0^a\int_0^b U_H(.)g_m(\theta;m,\Delta)d\theta f(\Delta;t,e_L)d\Delta\right]$$

$$-\mu\left[\int_0^a\int_0^b U_L(.)g_m(\theta;m,\Delta)d\theta f(\Delta;t,e_L)d\Delta\right]=0,$$

where $g_m(\theta;m,\Delta)=\dfrac{\partial g(\theta;m,\Delta)}{\partial m}$. Rearranging terms, (2.17) becomes

$$\phi\left[\int_0^a\int_0^b \chi(\theta,\alpha)g_m(\theta;m,\Delta)d\theta f(\Delta;t,e_H)d\Delta+r\right]=$$

$$(\lambda+\mu)\left[\int_0^a\int_0^b U_H(.)g_m(\theta;m,\Delta)d\theta f(\Delta;t,e_H)d\Delta\right]-\mu\left[\int_0^a\int_0^b U_L(.)g_m(\theta;m,\Delta)d\theta f(\Delta;t,e_L)d\Delta\right].$$

Then, the first-order condition for the number of auditing samples $m$ is given by

**(2.18)**

$$\frac{1}{\int_0^a\int_0^b U_H(.)g_m(\theta;m,\Delta)d\theta f(\Delta;t,e_H)d\Delta}=\frac{\lambda}{\phi}\frac{1}{\int_0^a\int_0^b \chi(\theta,\alpha)g_m(\theta;m,\Delta)d\theta f(\Delta;t,e_H)d\Delta+r}$$

$$+\frac{\mu}{\phi}\frac{1}{\int_0^a\int_0^b \chi(\theta,\alpha)g_m(\theta;m,\Delta)d\theta f(\Delta;t,e_H)d\Delta+r}\left[1-\frac{\int_0^a\int_0^b U_L(.)g_m(\theta;m,\Delta)d\theta f(\Delta;t,e_L)d\Delta}{\int_0^a\int_0^b U_H(.)g_m(\theta;m,\Delta)d\theta f(\Delta;t,e_H)d\Delta}\right].$$

Note here that the condition is a function of the incentive payment, the price of auditing one lot, and the marginal rate of substitution for working less versus working more.

Similarly, the first-order condition for training $t$ is obtained in the same way. Thus,

**(2.19)** $$\frac{\partial L}{\partial t}=\int_0^a \Delta f_t(\Delta;t,e_H)d\Delta-\phi\left[\int_0^a\left[1+\int_0^b C(.)f_t(\Delta;t,e_H)\right]d\Delta\right]$$

$$+\lambda\left[\int_0^a\int_0^b U'_H(.)I_t(\theta,t,e_H)g(\theta;m,\Delta)d\theta f(\Delta;t,e_H)d\Delta + U_H(.)g(\theta;m,\Delta)d\theta f_t(\Delta;t,e_H)d\Delta\right]$$

$$+\mu\left[\int_0^a\int_0^b U'_H(.)I_t(\theta,t,e_H)g(\theta;m,\Delta)d\theta f(\Delta;t,e_H)d\Delta + U_H(.)g(\theta;m,\Delta)d\theta f_t(\Delta;t,e_H)d\Delta\right]$$

$$-\mu\left[\int_0^a\int_0^b U'_L(.)I_t(\theta,t,e_L)g(\theta;m,\Delta)d\theta f(\Delta;t,e_L)d\Delta + U_L(.)g(\theta;m,\Delta)d\theta f_t(\Delta;t,e_L)d\Delta\right] = 0.$$

where $C = w + rm + t + \int_0^b \chi(\theta,\alpha)g(\theta;m,\Delta)d\theta$ and $f_t = \dfrac{\partial f(\Delta;t,e)}{\partial t}$. Rearranging terms, we get

$$\phi\int_0^a\left[1+\int_0^b C(.)f_t(\Delta;t,e_H)\right]d\Delta - \int_0^a \Delta f_t(\Delta;t,e_H)d\Delta =$$

$$[\lambda+\mu]\left[\int_0^a\int_0^b U'_H(.)I_t(\theta,t,e_H)g(\theta;m,\Delta)d\theta f(\Delta;t,e_H)d\Delta + U_H(.)g(\theta;m,\Delta)d\theta f_t(.)d\Delta\right]$$

$$-\mu\left[\int_0^a\int_0^b U'_L I_t(\theta,t,e_L)g(\theta;m,\Delta)d\theta f(\Delta;t,e_L)d\Delta + U_L(.)g(\theta;m,\Delta)d\theta f_t d\Delta\right].$$

Then, the first-order condition for the training scheme $t$ is

**(2.20)**

$$\frac{1}{\int_0^a\int_0^b U'_H(.)I_t(\theta,t,e_H)g(\theta;m,\Delta)d\theta f(\Delta;t,e_H)d\Delta + U_H(.)g(\theta;m,\Delta)d\theta f_t(.)d\Delta} =$$

$$\frac{\lambda}{\phi\int_0^a\left[1+\int_0^b C(.)f_t(\Delta;t,e_H)\right]d\Delta - \int_0^a \Delta f_t(\Delta;t,e_H)d\Delta}$$

$$+\frac{\mu}{\phi\int_0^a\left[1+\int_0^b C(.)f_t(\Delta;t,e_H)\right]d\Delta - \int_0^a \Delta f_t(\Delta;t,e_H)d\Delta}\times$$

$$\left[1-\frac{\int_0^a\int_0^b U'_L(.)I_t(\theta,t,e_L)g(\theta;m,\Delta)d\theta f(\Delta;t,e_L)d\Delta+U_L(.)g(\theta;m,\Delta)d\theta f_t(.)d\Delta}{\int_0^a\int_0^b U'_H(.)I_t(\theta,t,e_H)g(\theta;m,\Delta)d\theta f(\Delta;t,e_H)d\Delta+U_H(.)g(\theta;m,\Delta)d\theta f_t(.)d\Delta}\right].$$

This result may suggest that training may be influenced by the expected pricing accuracy, the expected cost, and the sum of the marginal rate of substitution and the utilities from working less versus working more.

In general, note that the multipliers $\phi, \lambda, \mu$ must be strictly positive for the first-order conditions to hold. Given the complexity of the first-order conditions, it is not possible to derive the optimal training-auditing policy $(w^*, \alpha^*, m^*, t^*)$ from simultaneity. Unless more restrictive assumptions are made, the first-order conditions may be used to plot the shape of each choice variable as done in Varian.

We can conclude from this chapter that an optimal training-auditing policy may be influenced by the preferences of the grader, the density functions of the imperfect statistical signal of effort and the pricing error, the grader's effort choices, the price of auditing one lot, and the incentive payment scheme. Hence, internal or external sanctions matter. If the grader really perceives that higher effort levels lead to higher pricing accuracy (or lower expected pricing errors), then formal training programs such as workshops, seminars, conferences should emphasize the importance of following the norm in peanut grading. That is, the need to take cleaned samples as close to 500g as possible. Hence, the grader has to apply his or her high effort levels when weighing cleaned samples. Also, formal training programs could also help internalize sanctions and create consciousness and/or awareness of the problems deriving from taking overweight cleaned samples. However, the challenge still is how to get information on, for example, measures of pricing accuracy and all the variables set up in the proposed model given the current USDA's organizational structure and resources available.

# CHAPTER III

# DATA AND PROCEDURES

Previous studies have not considered the effects of overweight cleaned samples and the randomness introduced by the use of rounding of grade percentages on peanut prices. However, because of the lack of data on the key variables that account for the measurement variance $V_m$ such as cleaned sample weights, there was a need to develop a designed experiment. Recall that, under the current U.S. peanut grading system, cleaned sample weights are not recorded on the FV-95 inspection certificate. The experiment generated observations on cleaned sample weights in grams, grade percentages, the weight discrepancy in grams, and associated prices per ton in dollars. Foreign material (FM) and loose shelled kernels (LSK), that basically affect the sampling variance $V_S$, were not measured.

This chapter[2] presents the designed experiment that generated the data for objectives 3 through 6, a brief description of the peanut grading and pricing procedures followed to calculate grade percentages and prices per ton, and the procedures used to test the hypotheses related to objectives 3 through 7.

[2] Because of the numerous symbols needed, a few symbols are given new definitions in this chapter.

The repeated-measures experimental design is used to test the effects of overweight cleaned samples and the weight discrepancy on prices and grade factors measured (objectives 3 and 4). The paired-differences experimental design is used to test the effects of the use of rounding of grade percentages on the variability of prices (objective 5). Nonparametric and parametric methods are used to estimate the probability of regrading with and without rounding (objective 6). With the data provided by a major U.S. peanut buyer, we provide some evidence that official graders may take overweight cleaned samples (objective 7).

### *Data*

The experiment that generated the data used to formally test the hypotheses regarding objectives 3 through 6 was carried out at the buying point of Colvin, Oklahoma, owned by the Texoma Peanut Company, a division of The Clint Williams Company, from January 21 to January 24, 1997. Grade factors were measured by three professional graders with the help of two faculty members of the Oklahoma State University. The graders were asked to complete the grade factor measurements quickly to simulate conditions during the peak of the grading season. The experiment used eighty-three 2,100g samples of peanuts collected from grading stations across the state of Oklahoma during the 1996 harvest season. The samples were taken from dryer wagons containing about 8,000 pounds (4 tons) of peanuts with a pneumatic probe. Fifty-eight samples were of spanish peanuts and twenty-five samples were of runner peanuts, respectively. The samples included a range of quality and cleanliness characteristics.

Each 2,100g sample was then divided into four 525g subsamples. The subsamples were split using a FSIS mechanical divider that is designed to maintain uniformity within the samples. The subsamples were coded by truckload from 1 to 83, size "A", "B", "C", and "D", peanut type (SP for spanish and R for runner), and the grader who made the analysis. The subsample sizes "A", "B", "C", and "D" were adjusted to within one peanut pod weight of 500, 501.4, 503.7, and 505g, respectively. This was done to have four different subsample sizes from the same sample. The database generated by the experiment is shown in Appendix B.

The data used to test the hypothesis related to objective 7 come from the records kept by a major U.S. peanut buyer. The buyer recorded official grade factors from all purchases by peanut type for a year. Most of the official grades were based on truckloads at individual buying points. Grade factors measured by the buyer's own graders or private graders were based on semi-trailer loads either received at one of the buyer's processing plants or warehouses. The sample for re-measuring grade factors (regrades) was drawn within two days of the sample for the official grade. The data collected by the buyer were used to provide some evidence that, on average, official graders may take overweight cleaned samples in the U.S. peanut industry.

Since the grade factor measurement used in the experiment followed the standard U.S. peanut grading procedure (USDA, 1996; Dickens and Johnson), we briefly describe the standard grading and pricing procedure before addressing the procedures and techniques for each objective.

***The Standard U.S. Peanut Grading and Pricing Procedure***

The grading procedure specifies that the grader draws about a 3,600g sample from random locations of the truckload using a pneumatic sampler or a spout sampler. Usually, the grader rotates among a set of sampling patterns. Sometimes a diverter sampler is used and sometimes the samples are taken from sacks. The sample is then divided into two 1,800g subsamples using a sample divider. One subsample is graded (work subsample) and the another one is held as a check (check subsample). After foreign material (FM), debris such as sticks and rocks, and loose shelled kernels (LSK), kernels shelled by harvesting and handling before marketing, are removed, 500g (1.1 lb) of cleaned pods, the so-called cleaned sample, are passed through the presizer if the size of the load is 10 tons or less. For single loads of over 10 tons, a 1,000g (2.2 lb) cleaned sample is used. Note that the cleaned sample begins with peanuts still in the shell. Unlike most grains, peanuts are partially processed (shelled) before grading. After shelling the cleaned sample in the sampler sheller, the kernels are sized, sampled for moisture content (MC) and separated into three categories. In the case of runner peanuts, the categories are kernels which ride a 16/64 by 3 / 4 inch slotted screen (+16's); kernels that fall through the screen (-16's); and split kernels (Dowell, Konstance, and Meyer). The grading screen used in the sizer changes with peanut type.

In general, the grade factors or characteristics measured on the basis of the kernels in each category are the percentages of sound mature kernels (SMK), undamaged edible kernels; sound splits (SS), edible kernels split in half during shelling; damaged kernels (DK), kernels discolored by freezing, insects or molds like *Aspergillus flavus* (*A. flavus*); and other kernels (OK), small inedible kernels (Dowell, Meyer and Konstance, 1994a). In addition, the percentages of concealed rancidity, mold or decay (RMD), freeze damage (FD), total damage and total kernels are also measured. For virginia peanuts, extra large kernels (ELK), which are part of SMK, are measured. Also, hulls are weighed and saved to check the accuracy of the grade factors measured. All kernels are examined for visible A. *flavus*, which is an indirect indication of aflatoxin, a suspected carcinogen. Detection of A. *flavus* mold growth on any kernel in the cleaned sample implies the rejection of the entire truckload. If so, peanuts are crushed for oil and are devaluated by about 75 percent (Dowell, 1992).

The grader calculates the grade percentages either by hand or using a calculator. For example, the percentage of sound mature kernels ($\%SMK$) is calculated by dividing the weight of sound mature kernels in grams by 500g and multiplied it by 100. The percentage of sound mature kernels (%SMK) is rounded to the nearest whole number before it is entered into the FV-95 inspection certificate. That is,

**(3.1)**
$$\%SMK = \text{round}\left(\frac{\text{Weight of SMK}}{500}\right)\times 100 .$$

The grade factors used for pricing purposes are the percentages of sound mature kernels (%SMK), sound splits (%SS), and other kernels (%OK). The sum of the percentages of sound mature kernels (%SMK) and sound splits (%SS) is the percentage of total sound mature kernels (%TSMK), the primary factor in peanut pricing. There are financial penalties for damaged kernels (DK) over 1 percent, and sound splits (%SS) over 4 percent.

With this information the buyer calculates the price per ton using a formula where each grade factor has an associated price appearing in a table. The price per ton paid to the producer $(PRICE)$ in dollars is then given by

$$PRICE = P_{TSMK} \cdot \%TSMK + P_{OK} \cdot \%OK - P_{ESS} \cdot [\max(\%SS - 4), 0], \quad \textbf{(3.2)}$$

where $P_{TSMK} = \$8.581$ is the price per ton for percent of total sound mature kernels, $P_{OK} = \$1.4$ is the price per ton for percent of other kernels, and $P_{ESS} = \$0.8$ is the financial penalty for sound splits over 4 percent. The dollar value of the load excluding loose shelled kernels (LSK) is obtained by multiplying the price per ton and the net weight of the truckload, which is gross weight less foreign material (FM) and excess moisture. Recall that the estimates of foreign material (FM), which mainly affect the dollar value of the load, are not measured from the cleaned sample, but from the 1,800g work subsample.

Then, the truckload is purchased and subsequently shelled or processed into edible products (Segregations I and II) or crushed for peanut oil (Segregation III). The size of truckloads generally ranges from 4 to 20 tons. The buyer provides the equipment used in the grading process and the grader's salary. Grading fees are \$4.00 per ton and there is a \$32.00 per hour extra charge if grading is done during overtime. Grading takes about 20 minutes/sample. There is no charge for regrading done during working hours. On average, the grader grades 25 samples/day.

***Procedure for Objective 3: Effects of Overweight Cleaned Samples on the Price per Ton Paid to Producers***

Data used for testing objective 3 were generated by following a repeated-measures experimental design. That is, the professional graders obtained repeated measurements of the same variables in the same units. The experiment generated observations over truckloads on cleaned sample weights in grams, grade factors, the weight discrepancy in grams, and associated prices per ton in dollars. We want to analyze this cross-section data in a special way to get efficiency of the parameter estimates of the regression models (Greene).

To test the effects of overweight cleaned samples on the price per ton paid to producers, fixed and random effects models are used. The fixed effects model assumes that differences introduced by sampling eighty-three different truckloads and having four observations on each truckload (subsample sizes) are captured by differences in the intercept. To formally test the effects under the fixed effects model, the following linear and logarithmic regression models are estimated.

The linear price equation is given by

**(3.3)**
$$PRICE_{ij} = \alpha_0 + \sum_{i=1}^{82} \alpha_{1i} LOAD_i + \alpha_2 SAMPLE_{ij} + \varepsilon_{ij}$$

$$\text{for } i = 1, \ldots, 82 \text{ and } j = 1, \ldots, 4,$$

where $PRICE_{ij}$ is the price per ton in dollars of the *ith* truckload and *jth* subsample size based on rounding/500g cleaned sample, $LOAD_i$ is a fixed effect or dummy variable for the *ith* truckload, $SAMPLE_{ij}$ is the cleaned sample weight in grams, and $\varepsilon_{ij}$ is the unique error term assumed to be normally distributed. The overall intercept $\alpha_0$ is adjusted by each $\alpha_{1i}$ so that eighty-two truckload specific intercepts are obtained. Equation (3.3) is also estimated with prices based on no rounding/500g cleaned sample.

Similarly, the logarithmic price equation is

**(3.4)** $$LOGPRICE_{ij} = \alpha_0 + \sum_{i=1}^{82} \alpha_{1i} LOAD_i + \alpha_2 LOGSAMPLE_{ij} + \varepsilon_{ij}$$

for $i = 1, ..., 82$ and $j = 1, ..., 4$,

where $LOGPRICE_{ij}$ and $LOGSAMPLE_{ij}$ are the logarithms of the price per ton in dollars and the cleaned sample weight in grams, respectively, as defined in equation (3.3). Also, as mentioned above, equation (3.4) is estimated with prices based on no rounding/500g cleaned sample. Parameters in equations (3.3) and (3.4) are estimated with the PROC GLM in SAS (SAS Institute). For example, the SAS statements for equation (3.3) are:

```
PROC GLM;
        CLASS LOAD;
                MODEL PRICE = LOAD SAMPLE / SOLUTION;
```

Under the random effects or error component approach, the model assumes that there is an overall intercept $\alpha_0$ and an error term with two components: $\tau_i + \varepsilon_{ij}$. Here, $\tau_i$ represents the extent to which the intercept of the *ith* truckload differs from the overall intercept (Kennedy). The model in (3.3) and (3.4) can be reformulated as

**(3.5)** $$PRICE_{ij} = \alpha_0 + \alpha_1 SAMPLE_{ij} + \tau_i + \varepsilon_{ij},$$

and

**(3.6)** $$LOGPRICE_{ij} = \alpha_0 + \alpha_1 LOGSAMPLE_{ij} + \tau_i + \varepsilon_{ij}.$$

We expect that $\alpha_2 = 1$ in equation (3.4) and $\alpha_1 = 1$ in equation (3.6) to test the null hypothesis that the elasticity of the cleaned sample weight is one. Parameters in equations (3.5) and (3.6) are estimated using PROC MIXED in SAS (SAS Institute). The SAS statements for equation (3.5) are:

```
PROC MIXED;
        CLASS LOAD;
                MODEL PRICE = SAMPLE / SOLUTION;
                        REPEATED / TYPE = CS   SUBJECT = LOAD;
```

Also, descriptive statistics of prices based both on rounding and no rounding, for each of the four subsample sizes, are presented.

***Procedure for Objective 4: Effects of Overweight Cleaned Samples and the Weight Discrepancy on Grade Factors Measured***

To test the effects of overweight cleaned samples and the weight discrepancy on grade factors measured, equations for sound mature kernels (SMK), sound splits (SS), other kernels (OK), total damage (TD) and hulls are estimated in the same fashion like for equations (3.3) and (3.5). For example, the equations for SMK expressed in grams with fixed and random effects models are:

**(3.7)** $$SMK_{ij} = \beta_0 + \sum_{i=1}^{82} \beta_{1i} LOAD_i + \beta_2 SAMPLE_{ij} + \beta_3 DISCREPANCY_{ij} + \nu_{ij},$$

and

**(3.8)** $$SMK_{ij} = \beta_0 + \beta_1 SAMPLE_{ij} + \beta_2 DISCREPANCY_{ij} + \upsilon_i + \nu_{ij},$$

where $SMK_{ij}$ is the weight of sound mature kernels in grams measured from the *ith* truckload and *jth* subsample size, $LOAD$ and $SAMPLE$ are as defined above,

$DISCREPANCY_{ij}$ is the weight discrepancy in grams related to the *ith* truckload and *jth* subsample size, $\nu_{ij}$ is the error term under the fixed effects model, and $\upsilon_i + \nu_{ij}$ is the error term under the random effects model. We expect that the sum of the slope coefficients of $SAMPLE$ under the fixed and random effects models is $+1$. However, we expect a negative relationship between grade factors and the weight discrepancy. So, the sum of the slope coefficients of $DISCREPANCY$ is $-1$.

***Procedure for Objective 5: Variability of Prices Introduced by the Use of Rounding of Grade Percentages***

We argue that rounding makes the measurement of grade factors, and thus prices, less accurate. We test that rounding introduces noise into the price measurement using a paired-differences experimental design framework. Paired-differences experimental designs are used to increase the information in an experiment by decreasing the background noise (variation) caused by uncontrolled nuisance variables (Mendenhall, Wackerly, and Scheaffer).

We compare four peanut pricing methods to estimate the variability of prices introduced by the use of rounding. Method A is the current U.S. peanut pricing method; that is, the price per ton $(PRICE_A)$ is calculated based on grade percentages with rounding/500g cleaned sample. Method B is similar to method A, but the price per ton $(PRICE_B)$ is calculated based on grade percentages with no rounding/500g cleaned sample. Methods C and D are the equivalent of methods A and B, but prices are based on grade percentages with rounding/actual cleaned sample, and no rounding/actual cleaned sample, respectively. We are interested in testing the hypotheses that the averaged prices from methods A and B, A and C, C and D, and B and D differ due to overweight cleaned samples and the use of rounding of grade percentages. Specifically, we expect that rounding will contribute to the variability of prices.

For example, the paired-difference experiment uses information on the *hth* paired differences for methods A (rounding/500g cleaned sample) and B (no rounding/500g cleaned sample). So, we have $h$ paired observations in each block of prices given by

**(3.9)** $$D_h = PRICE_{Ah} - PRICE_{Bh}, \qquad \text{for } h = 1, \ldots, N$$

where $D_h$ is the *hth* paired difference, $PRICE_{Ah}$ is the *hth* price based on method A, and $PRICE_{Bh}$ is the *hth* price based on method B, respectively. Paired differences for the other treatments are obtained in the same fashion. The purpose of the experiment is to make inferences on the differences between the means of the two pricing methods, say $\mu_A - \mu_B$, from the mean of the differences, $\mu_d$.

The expected value of the *hth* paired difference is given by

$\mu_d = E[D_h] = E[PRICE_{Ah} - PRICE_{Bh}] = E[PRICE_{Ah}] - E[PRICE_{Bh}]$ or $\mu_d = \mu_A - \mu_B$, with the mean of the paired differences defined as

**(3.10)** $$\bar{D} = \frac{1}{N}\sum_{h=1}^{N} D_h$$

and the sample variance of the $N$ differences is

**(3.11)** $$\sigma_d^2 = \frac{1}{N-1}\sum_{h=1}^{N}(D_h - \bar{D})^2 .$$

The variability of prices is given by the standard deviation $\sigma_d$ of the paired differences. Since the number of differences is large $(N > 30)$, the large sample inferential method is used. Under the assumption that the differences are normally distributed, the null hypothesis of average prices being the same under the methods A and B is $\mathrm{H}_0 : \mu_A - \mu_B = \mu_d = 0$. This is tested by using Student's $t$ statistic

$$t = \frac{\bar{D} - \mu_d}{\sigma_d / \sqrt{N}}. \tag{3.12}$$

We use a two-tailed test since we are testing that the two methods differ. Based on $N-1$ degrees of freedom and a 5% significance level, we calculate the critical value of the test statistics. If the observed value of $t$ lies in the rejection region, we reject the null hypothesis that $\mu_A - \mu_B = 0$ and conclude that the two methods have different average responses. If the alternative hypothesis is true, the distributions of both prices are the same, but $\mu_A$ is larger than $\mu_B$ or vice versa. If $\mu_A > \mu_B$, the distribution of $PRICE_A$ is shifted to the right of the distribution of $PRICE_B$. The means and the standard deviations of the paired differences are obtained using PROC MEANS in SAS (SAS Institute).

***Procedure for Objective 6: Estimation of the Probability of Regrading***

We estimate the probability of regrading $\Gamma$ using nonparametric and parametric methods. Under the nonparametric method, the probability of regrading $\Gamma$ is estimated using the empirical p.d.f. method. That is, the probability of regrading is calculated by dividing the observed number of subsamples in each size that falls outside of the 99-101% range by the total number of subsamples in each size. Parametric methods are used to model problems where the distribution of the random variable is previously specified except for the values of a finite set of parameters. Otherwise, nonparametric methods are applied (Mendenhall, Wackerly, and Scheaffer).

The parametric approach to the probability of regrading with and without rounding of grade percentages considers the use of a multiple-dimension integral and a new probability distribution, respectively. We assume that the grader does not make errors when grading, but when the grader does so, these errors may be large. These large errors are captured by the weight discrepancy $W$ in grams that can take positive and negative values. To estimate the probability of regrading without rounding $\Gamma_{NR}$ we need the density function for the weight discrepancy in grams $Z(W)$. We also assume that, as specified in chapter 2, this random variable combines two sources of errors. One source is associated with the randomness introduced by the weight lost as dust and kernels during grading. The other source is associated with the randomness introduced by infrequent equipment and human errors.

Given these specific characteristics, we assume that the weight discrepancy $W$ in grams follows a new probability distribution called a "normal-jump distribution". This distribution is a modification of the mixed diffusion-jump process that has been considered as a model of asset prices (Steigert and Brorsen; Yang and Brorsen) and of exchange rate movements (Akgiray and Booth [1986, 1988]; Oldfield, Rogalski, and Jarrow; Tucker and Pond). The major difference is that a normal distribution is used rather than the lognormal that is usually used to represent the diffusion process.

The normal-jump distribution combines a normally distributed process and a jump process. We assume that the process associated with weight lost follows a normal distribution with mean $\alpha$ and variance $\sigma_N^2$. The process associated with infrequent equipment and human errors is assumed to be described by a Poisson distribution with mean $\mu$ and variance $\sigma_J^2$ that measures the size of the jump or error. The jump intensity $\lambda \geq 0$ indicates the probability of occurrence of a jump; that is, a large equipment or human error. The jump process is assumed to be independent of the normal process. Yang and Brorsen point out that the distribution is skewed if $\mu$ is not zero and the direction of skewness is the same as the sign of $\mu$. The distribution is leptokurtic if $\lambda$ is greater than zero.

The density function for weight discrepancy $W$ in grams for the normal-jump distribution is given by

$$\text{(3.13)} \qquad Z(W;\theta) = \sum_{n=0}^{\infty}\left[\frac{\exp^{-\lambda}}{n!}\lambda^{n}\right]\left[\frac{\exp^{-[W_r-(\alpha+n\mu)]^2 / 2(\sigma_N^2+n\sigma_J^2)}}{\sqrt{2\pi(\sigma_N^2+n\sigma_J^2)}}\right],$$

$$\text{for } r = 1, \ldots, Q$$

where $\theta$ is the vector of five parameters of the normal-jump stochastic process, and $Q$ is the number of observations on weight discrepancy in grams. The summand tends to zero as $n$ increases. For estimation purposes, the summation is calculated up to $n = 7$.

The likelihood function, $\Omega$, is as follows:

$$\text{(3.14)} \qquad \Omega = \prod_{t=1}^{n} \sum_{n=0}^{\infty} \frac{1}{\sqrt{2\pi(\sigma_N^2+n\sigma_J^2)}}\left[\left(\frac{\exp(-\lambda)}{n!}\right)\lambda^{n}\right]\exp\left[-\frac{[W_r-(\alpha+n\mu)]^2}{2(\sigma_N^2+n\sigma_J^2)}\right].$$

The estimation problem is to maximize the log-likelihood function $\operatorname{Ln}\Omega$ with respect to the five parameters: $\alpha$, $\sigma_N^2$, $\lambda$, $\mu$, and $\sigma_J^2$. The estimation of this nonlinear model requires the use of a numerical optimization algorithm. The procedure also requires calculating the likelihood function, $\Omega$, and its gradient (first derivative) at each iteration. SHAZAM uses a quasi-Newton method known as a variable metric method. The Hessian (second derivatives) inverse approximation is obtained in each iteration by an updating scheme that involves adding a correction matrix. At model convergence, this approximation could be used as the covariance matrix estimate of the estimated parameters (White). Therefore, the numerical Hessian matrix is computed using the NUMCOV option in SHAZAM. However, this procedure might not provide the most accurate standard errors. The parameters in equation (3.13) are estimated using the NL command and the LOGDEN option in SHAZAM.

Likelihood ratio tests are used to test the superiority of the proposed normal-jump distribution. The model is compared to models given by a pure normal, Gamma, and Student *t*-distributions. For example, a test of the hypothesis that the normal-jump distribution is superior to a pure normal process is to test that the weight discrepancy is normally distributed and, therefore, there is no jump process. The null hypothesis is $\mathrm{H}_0 : \mu = \sigma_J^2 = \lambda = 0$. Denoting $\mathrm{Ln}\,\Omega_R$ as the log-likelihood function of the restricted model (pure normal process) and $\mathrm{Ln}\,\Omega_U$ that of the unrestricted model (normal-jump stochastic process), the statistic $-2[\mathrm{Ln}\,\Omega_R - \mathrm{Ln}\,\Omega_U]$ is approximately chi-square distributed with three degrees of freedom.

The density function for weight discrepancy in grams $Z(W)$ is then used to estimate the probability of regrading without rounding of grade percentages $\Gamma_{NR}$ for a set of cleaned sample weights $S$, given $W$ and $\theta$. This probability is given by

$$\Gamma_{NR} = 1 - \int_{S-505}^{S-495} Z(W; S, \theta) dW. \tag{3.15}$$

The MAPLE 5.3 mathematical program is used to numerically evaluate the integral in (3.15) (Char et al.).

The probability of regrading with rounding $\Gamma_R$ is calculated using a multiple-dimension integral

$$\Gamma_R = 1 - \int\int\int\int\int I_{[99,101]}[j' \text{round}(G)] p(G; S, W) dG \, Z(W; S, \theta) dW \tag{3.16}$$

where $I_{[99,101]}[.]$ is an indicator function that is one when the argument is inside the interval and zero otherwise, $j'$ is a 1x5 vector of ones, round(G) is a 5x1 vector of grade factors such as sound mature kernels (SMK), sound splits (SS), other kernels (OK), total damage (TD), and hulls, expressed in percentages and rounded to the nearest whole number, $p(G; S, W)$ are the joint density functions for the grade factors mentioned, and $Z(W; S, \theta)$ is the density function for weight discrepancy in grams as defined above. The lower and upper limits of the integrals are 0 and 100, respectively.

The multiple integral in (3.16) is calculated with Monte Carlo integration. Monte Carlo integration uses stochastic simulation to generate a number of values of the weight discrepancy in grams $W$ and the grade factors $G$ conditional on the cleaned sample weight $S$. The integral then is the percentage of times that regrading was necessary given the stochastically generated grade factors. Ten thousand replications are used.

***Procedure for Objective 7: Differences in Average Grade Factors and Prices Measured by Official and Private Graders in an Actual Situation***

To provide some evidence that graders may take overweight cleaned samples, we calculate the differences in average grade factors and prices calculated by official and private graders in an actual situation. The data used were provided by a major U.S. peanut buyer. The data contain the average official grade factors corresponding to purchases from all buying points for a year. Also, the data provide the average grade factors measured by the buyer's own graders, also known as private graders, from samples taken from all purchases. Official grade factors are based on truckloads at individual buying points. Regraded peanuts (regrades) are based on semi-trailer loads either received at one of the firm's processing plants or warehouses. The samples for regrades are drawn within two days of the sample for the official grade.

Differences between average official and private grade factors could provide some evidence that official graders may take overweight cleaned samples. The average actual cleaned sample in grams taken by official graders is calculated as

**(3.17)** $$\text{Average Actual Cleaned Sample} = \frac{\text{Official Average Grade Factors}}{\text{Private Average Grade Factors}} x\, 500,$$

where official average grade factors is the average of the total sum of grade factors (SMK, SS, OK, and TD) measured by official graders, and private average grade factors is the average of the total sum of grade factors measured by private graders. The results showing the differences by grade factors and peanut type are also graphically presented since they can be used in extension and formal training programs for peanut graders.

Under the assumption that the information and methods provided by the peanut buyer reflect the current state of the U.S. peanut industry, differences between average official and private prices could provide an approximation to the impact of taking overweight cleaned samples at the industry level.

# CHAPTER IV

# EMPIRICAL RESULTS

The empirical results obtained in this chapter show that taking overweight cleaned samples does result in higher prices. However, rounding does not affect expected prices or expected grade factors. Rounding does introduce noise and does slightly increase the probability of regrading.

## *Objective 3: Effects of Overweight Cleaned Samples on the Price per Ton Paid to Producers*

Table 4.1 provides descriptive statistics of the price per ton paid to producers for each of the four subsample sizes. Prices were calculated based on grade percentages with rounding/500g cleaned sample, no rounding/500g cleaned sample, rounding/actual cleaned sample, and no rounding/actual cleaned sample. Prices based on grade percentages with rounding/500g cleaned sample, as currently done by the USDA, increase and tend to be higher as the cleaned sample weight increases (Figure 4.1).

However, prices based on grade percentages with rounding/actual cleaned sample and no rounding/actual cleaned sample show no consistent pattern (Figure 4.2). The pattern shown suggests that the USDA could easily correct the problem of taking

**Table 4.1. Descriptive Statistics of Grade Factors and Prices by Subsample Size**

| Description | Sound Mature Kernels | Sound Splits | Total Sound Mature Kernels | Other Kernels | Total Damage | Total Kernels | Hulls | Total Kernels and Hulls | Price per Ton in Dollars |
|---|---|---|---|---|---|---|---|---|---|
| ***Size A=500.0g*** | | | | | | | | | |
| *Rounding/500g Cleaned Sample* | | | | | | | | | |
| Mean | 63.38 | 5.88 | 69.27 | 4.88 | 0.33 | 74.49 | 25.13 | 99.62 | 599.48 |
| Std. Deviation | 3.86 | 3.73 | 2.73 | 1.62 | 0.47 | 2.10 | 1.98 | 0.65 | 21.12 |
| Minimum | 51.00 | 1.00 | 63.00 | 2.00 | 0.00 | 72.00 | 21.00 | 99.00 | 554.60 |
| Maximum | 72.00 | 18.00 | 77.00 | 10.00 | 1.00 | 80.00 | 28.00 | 101.00 | 661.14 |
| *No Rounding/500g Cleaned Sample* | | | | | | | | | |
| Mean | 63.30 | 5.91 | 69.21 | 4.82 | 0.42 | 74.46 | 25.13 | 99.59 | 598.88 |
| Std. Deviation | 3.80 | 3.66 | 2.62 | 1.60 | 0.33 | 1.99 | 1.96 | 0.22 | 20.35 |
| Minimum | 50.70 | 1.16 | 63.40 | 2.42 | 0.00 | 71.16 | 20.54 | 99.02 | 558.20 |
| Maximum | 71.54 | 17.98 | 76.66 | 10.12 | 1.42 | 79.36 | 27.86 | 100.40 | 658.84 |
| *Rounding/Actual Cleaned Sample* | | | | | | | | | |
| Mean | 63.37 | 5.88 | 69.26 | 4.88 | 0.32 | 74.46 | 25.12 | 99.58 | 599.37 |
| Std. Deviation | 3.83 | 3.73 | 2.73 | 1.62 | 0.47 | 2.11 | 1.97 | 0.63 | 21.09 |
| Minimum | 51.00 | 1.00 | 63.00 | 2.00 | 0.00 | 72.00 | 21.00 | 99.00 | 554.60 |
| Maximum | 72.00 | 18.00 | 77.00 | 10.00 | 1.00 | 80.00 | 28.00 | 101.00 | 661.14 |
| *No Rounding/Actual Cleaned Sample* | | | | | | | | | |
| Mean | 63.32 | 5.93 | 69.24 | 4.83 | 0.42 | 74.49 | 25.10 | 99.59 | 599.15 |
| Std. Deviation | 3.83 | 3.68 | 2.62 | 1.61 | 0.33 | 1.97 | 1.95 | 0.20 | 20.32 |
| Minimum | 50.66 | 1.16 | 63.41 | 2.42 | 0.00 | 72.37 | 20.55 | 99.18 | 558.32 |
| Maximum | 71.58 | 17.97 | 76.61 | 10.12 | 1.42 | 79.31 | 27.13 | 100.32 | 658.45 |
| ***Size B=501.4g*** | | | | | | | | | |
| *Rounding/500g Cleaned Sample* | | | | | | | | | |
| Mean | 63.51 | 5.79 | 69.30 | 4.80 | 0.40 | 74.49 | 25.47 | 99.96 | 599.78 |
| Std. Deviation | 3.53 | 3.36 | 2.57 | 1.46 | 0.49 | 2.21 | 1.95 | 0.64 | 20.17 |
| Minimum | 53.00 | 2.00 | 63.00 | 2.00 | 0.00 | 71.00 | 21.00 | 99.00 | 554.60 |
| Maximum | 73.00 | 18.00 | 77.00 | 10.00 | 1.00 | 79.00 | 29.00 | 101.00 | 657.14 |
| *No Rounding/500g Cleaned Sample* | | | | | | | | | |
| Mean | 63.51 | 5.76 | 69.27 | 4.79 | 0.41 | 74.48 | 25.41 | 99.89 | 599.56 |
| Std. Deviation | 3.48 | 3.34 | 2.55 | 1.45 | 0.29 | 2.02 | 1.95 | 0.21 | 19.84 |
| Minimum | 53.40 | 1.52 | 62.90 | 1.80 | 0.00 | 70.46 | 20.54 | 99.28 | 553.94 |
| Maximum | 73.02 | 17.68 | 77.30 | 10.14 | 1.26 | 79.58 | 28.82 | 100.38 | 659.38 |
| *Rounding/Actual Cleaned Sample* | | | | | | | | | |
| Mean | 63.39 | 5.68 | 69.08 | 4.77 | 0.37 | 74.22 | 25.46 | 99.67 | 597.94 |
| Std. Deviation | 3.47 | 3.19 | 2.61 | 1.48 | 0.48 | 2.20 | 1.97 | 0.61 | 20.49 |
| Minimum | 53.00 | 2.00 | 63.00 | 2.00 | 0.00 | 70.00 | 20.00 | 99.00 | 554.60 |
| Maximum | 73.00 | 18.00 | 77.00 | 10.00 | 1.00 | 79.00 | 29.00 | 101.00 | 657.14 |
| *No Rounding/Actual Cleaned Sample* | | | | | | | | | |
| Mean | 63.32 | 5.75 | 69.08 | 4.79 | 0.41 | 74.27 | 25.28 | 99.55 | 597.88 |
| Std. Deviation | 3.47 | 3.34 | 2.52 | 1.46 | 0.29 | 1.97 | 1.92 | 0.19 | 19.56 |
| Minimum | 53.22 | 1.51 | 62.66 | 1.79 | 0.00 | 71.66 | 20.47 | 99.04 | 551.84 |
| Maximum | 72.77 | 17.63 | 77.02 | 10.10 | 1.26 | 79.29 | 27.70 | 100.04 | 657.03 |

**Table 4.1. Continued**

| Description | Sound Mature Kernels | Sound Splits | Total Sound Mature Kernels | Other Kernels | Total Damage | Total Kernels | Hulls | Total Kernels and Hulls | Price per Ton in Dollars |
|---|---|---|---|---|---|---|---|---|---|
| ***Size C=503.7g*** | | | | | | | | | |
| *Rounding/500g Cleaned Sample* | | | | | | | | | |
| Mean | 64.09 | 5.56 | 69.64 | 4.68 | 0.26 | 74.58 | 25.52 | 100.10 | 602.68 |
| Std. Deviation | 3.30 | 3.11 | 2.77 | 1.56 | 0.44 | 2.34 | 2.08 | 0.64 | 21.70 |
| Minimum | 55.00 | 1.00 | 62.00 | 3.00 | 0.00 | 68.00 | 20.00 | 99.00 | 547.42 |
| Maximum | 73.00 | 17.00 | 78.00 | 11.00 | 1.00 | 81.00 | 31.00 | 101.00 | 671.12 |
| *No Rounding/500g Cleaned Sample* | | | | | | | | | |
| Mean | 64.10 | 5.58 | 69.67 | 4.71 | 0.40 | 74.78 | 25.45 | 100.23 | 602.97 |
| Std. Deviation | 3.34 | 3.08 | 2.62 | 1.60 | 0.33 | 2.04 | 1.98 | 0.23 | 20.38 |
| Minimum | 54.54 | 0.88 | 62.24 | 2.52 | 0.00 | 71.02 | 20.08 | 99.48 | 550.07 |
| Maximum | 73.00 | 17.32 | 77.36 | 11.42 | 1.26 | 80.36 | 28.84 | 100.96 | 665.36 |
| *Rounding/Actual Cleaned Sample* | | | | | | | | | |
| Mean | 63.58 | 5.70 | 69.28 | 4.68 | 0.27 | 74.23 | 25.28 | 99.51 | 599.52 |
| Std. Deviation | 3.36 | 3.12 | 2.56 | 1.56 | 0.44 | 2.12 | 2.04 | 0.58 | 20.00 |
| Minimum | 54.00 | 1.00 | 62.00 | 3.00 | 0.00 | 70.00 | 20.00 | 99.00 | 547.42 |
| Maximum | 73.00 | 17.00 | 77.00 | 11.00 | 1.00 | 80.00 | 29.00 | 101.00 | 662.54 |
| *No Rounding/Actual Cleaned Sample* | | | | | | | | | |
| Mean | 63.71 | 5.52 | 69.23 | 4.64 | 0.40 | 74.26 | 25.29 | 99.55 | 599.10 |
| Std. Deviation | 3.31 | 3.09 | 2.61 | 1.56 | 0.33 | 2.04 | 1.97 | 0.20 | 20.33 |
| Minimum | 54.15 | 0.87 | 61.84 | 2.50 | 0.00 | 70.51 | 19.93 | 99.05 | 546.57 |
| Maximum | 72.55 | 17.20 | 76.79 | 11.35 | 1.25 | 79.77 | 28.63 | 100.34 | 660.50 |
| ***Size D=505.0g*** | | | | | | | | | |
| *Rounding/500g Cleaned Sample* | | | | | | | | | |
| Mean | 64.00 | 5.68 | 69.68 | 4.84 | 0.25 | 74.77 | 25.68 | 100.44 | 603.10 |
| Std. Deviation | 3.39 | 3.41 | 2.62 | 1.66 | 0.43 | 1.90 | 1.92 | 0.57 | 20.01 |
| Minimum | 51.00 | 1.00 | 63.00 | 3.00 | 0.00 | 70.00 | 21.00 | 99.00 | 556.00 |
| Maximum | 72.00 | 17.00 | 77.00 | 11.00 | 1.00 | 80.00 | 29.00 | 101.00 | 657.74 |
| *No Rounding/500g Cleaned Sample* | | | | | | | | | |
| Mean | 64.08 | 5.75 | 69.83 | 4.84 | 0.38 | 75.06 | 25.45 | 100.50 | 604.39 |
| Std. Deviation | 3.51 | 3.30 | 2.71 | 1.65 | 0.27 | 2.08 | 2.01 | 0.33 | 21.07 |
| Minimum | 51.22 | 1.16 | 63.24 | 2.60 | 0.00 | 70.58 | 20.52 | 99.32 | 557.53 |
| Maximum | 72.48 | 16.72 | 77.04 | 10.62 | 1.44 | 80.36 | 28.74 | 100.96 | 663.28 |
| *Rounding/Actual Cleaned Sample* | | | | | | | | | |
| Mean | 63.10 | 5.89 | 68.99 | 4.93 | 0.25 | 74.17 | 25.30 | 99.46 | 597.17 |
| Std. Deviation | 3.36 | 3.37 | 2.72 | 1.75 | 0.44 | 2.08 | 1.96 | 0.60 | 20.92 |
| Minimum | 51.00 | 1.00 | 62.00 | 3.00 | 0.00 | 72.00 | 20.00 | 99.00 | 547.42 |
| Maximum | 71.00 | 17.00 | 77.00 | 11.00 | 1.00 | 81.00 | 27.00 | 101.00 | 663.34 |
| *No Rounding/Actual Cleaned Sample* | | | | | | | | | |
| Mean | 63.36 | 5.78 | 69.14 | 4.83 | 0.38 | 74.36 | 25.19 | 99.54 | 598.43 |
| Std. Deviation | 3.40 | 3.29 | 2.62 | 1.64 | 0.27 | 1.98 | 1.95 | 0.20 | 20.25 |
| Minimum | 50.70 | 1.15 | 62.63 | 2.57 | 0.00 | 71.99 | 20.31 | 99.05 | 552.12 |
| Maximum | 70.86 | 16.54 | 76.28 | 10.52 | 1.42 | 79.53 | 27.38 | 100.10 | 656.74 |

Note: Total sound mature kernels (TSMK) is sound mature kernels (SMK) plus sound splits (SS). Total damage (TD) is damaged kernels (DK) plus damaged splits (DS). Total kernels is the sum of TSMK, other kernels (OK) and TD.

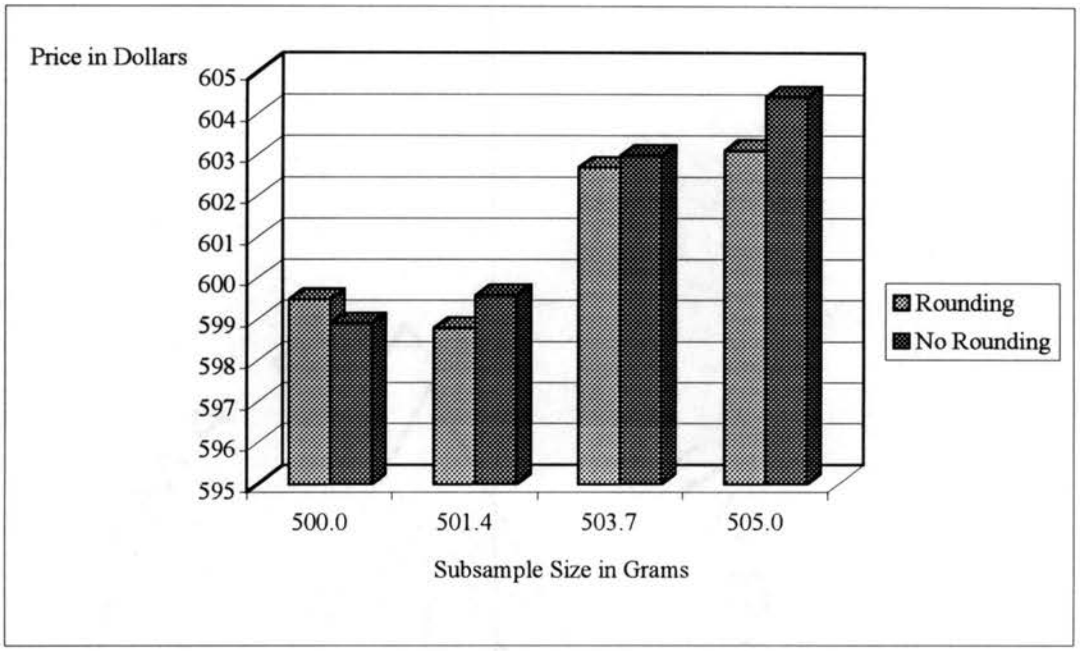


**Figure 4.1. Effect of the cleaned sample weight on the price per ton based on grade factors measured by assuming a cleaned sample of 500 grams was exactly taken**

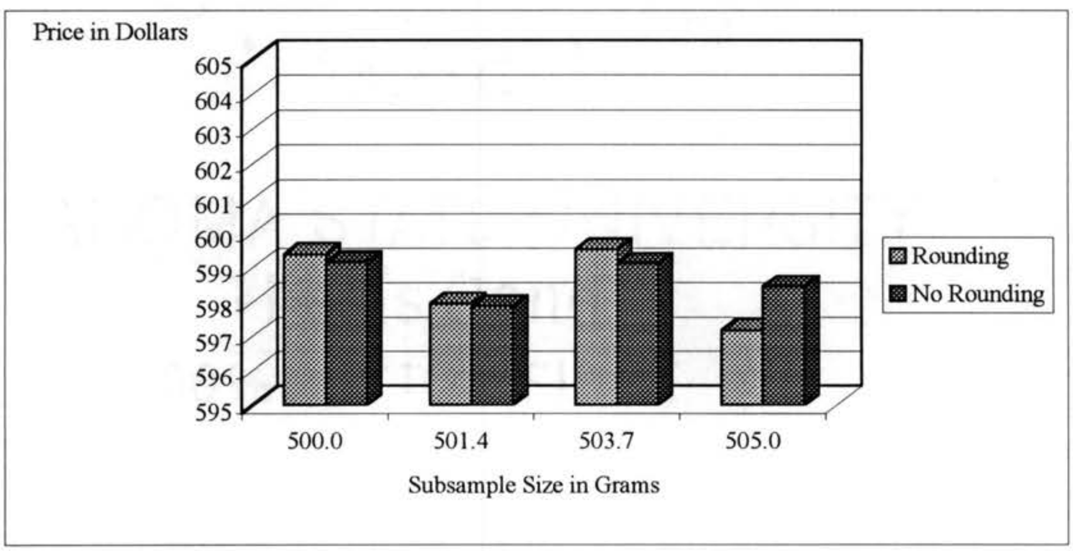


**Figure 4.2. Effect of the cleaned sample weight on the price per ton based on grade factors measured using the actual cleaned sample weight**

overweight cleaned samples by redesigning the peanut grading system to base grade percentages on the actual cleaned sample weights as is already done when measuring foreign material (FM). Note that rounding does not affect the means of prices. We expected slightly higher means of prices due to rounding. This could have probably been explained by more total kernels and hulls of 99%'s than of 101%'s are being lost due to negative skewness.

Table 4.2 reports the parameter estimates of the equations relating price to cleaned sample weights for linear and logarithmic functional forms following the fixed effects and random effects framework. The slope coefficients for cleaned sample weight clearly show that the price per ton has a statistically significant positive relationship with the cleaned sample weight. An additional one gram of cleaned sample increases the price by just over one dollar a ton. The estimates of the slope coefficients, with and without rounding, change only slightly. Thus, rounding does not remove the effect of larger cleaned sample weights. Apparently, any effect is too small to measure.

The null hypothesis that the elasticity of the cleaned sample weight in the logarithmic equations under fixed and random effects models is one is not rejected $(\mathrm{H}_0 : \alpha_1 = 1 \text{ in the logarithmic equation})$. Thus, there exists a one-to-one relationship between prices and cleaned sample weights. That is, a one percent increase in the cleaned sample weight results in a one percent increase in the price per ton paid to producers.

The variances of between-groups prices under the random effects models with and without rounding for the linear equations can be used as the variance of the imperfect statistical signal of effort $\theta$ mentioned in chapter 2. The variances of within-groups prices under the fixed and random effects models with and without rounding for the linear equations suggest that rounding introduces noise in peanut pricing. Note that whether fixed or random effects models are used does not really matter.

**Table 4.2. Parameter Estimates of the Price Equations with Fixed and Random Effects Models**

| | Fixed Effects | | | Random Effects | | |
|---|---|---|---|---|---|---|
| Parameter | Estimate | Standard Error | t-ratio | Estimate | Standard Error | t-ratio |
| Linear Equation – Rounding | | | | | | |
| Intercept | 101.0916 | 99.37 | 1.02 | 57.4447 | 99.51 | 0.58 |
| Cleaned Sample Weight | 1.0908 | 0.20 | 5.51 | 1.0816 | 0.20 | 5.46 |
| Between-Groups Variance | | | | 406.9776 | | |
| Within-Groups Variance | 44.7153 | | | 44.7656 | | |
| Linear Equation – No Rounding | | | | | | |
| Intercept | 49.2255 | 81.87 | 0.60 | 4.0853 | 81.83 | 0.05 |
| Cleaned Sample Weight | 1.1868 | 0.16 | 7.29 | 1.1883 | 0.16 | 7.30 |
| Between-Groups Variance | | | | 383.1375 | | |
| Within-Groups Variance | 31.1262 | | | 31.1210 | | |
| Logarithmic Equation – Rounding | | | | | | |
| Intercept | 0.8417 | 1.03 | 0.82 | 0.8111 | 1.03 | 0.79 |
| Cleaned Sample Weight | 0.9059 | 0.16 | 5.49 | 0.8983 | 0.16 | 5.45 |
| Between-Groups Variance | | | | 0.0011 | | |
| Within-Groups Variance | 0.0001 | | | 0.0001 | | |
| Logarithmic Equation – No Rounding | | | | | | |
| Intercept | 0.3325 | 0.85 | 0.39 | 0.2530 | 0.85 | 0.30 |
| Cleaned Sample Weight | 0.9868 | 0.14 | 7.26 | 0.9881 | 0.14 | 7.27 |
| Between-Groups Variance | | | | 0.0010 | | |
| Within-Groups Variance | 0.0000[1] | | | 0.0000[2] | | |

Note: Prices are calculated based on grade percentages with rounding/500g cleaned sample and no rounding/500g cleaned sample. LOAD dummies for the fixed effects models are not printed.
[1] The estimate is 0.00008598.
[2] The estimate is 0.00008596.

### *Objective 4: Effects of Overweight Cleaned Samples and the Weight Discrepancy on Grade Factors Measured*

Table 4.1 also provides descriptive statistics of all grade factors based on rounding/500g cleaned sample, no rounding/500g cleaned sample, rounding/actual cleaned sample, and no rounding/actual cleaned sample. Note that rounding does not affect the means of grade factors. Table 4.3 provides parameter estimates of the equations relating grade factors in grams to cleaned sample weights and the weight discrepancy with fixed and random effects models. All grade factors are with no rounding since the weight discrepancy in grams is a continuous variable. The results under the fixed and random effects models show that only sound mature kernels (SMK) and hulls have a statistically significant positive relationship with the cleaned sample weight. The other categories make up a small part of total weight and so their equations are estimated less accurately. Hence, taking increased cleaned samples will result in increased SMK, and thus in higher prices, and hulls. This is because SMK is the primary factor used in peanut pricing. Also, note that the sum of the slope coefficients for cleaned sample weight is always one as suggested when checking the accuracy of the grade factors measured.

Weight discrepancy has only a statistically significant negative relationship with SMK. The implication is that most of the large errors are in measuring SMK. That is, the grader is more likely to lose kernels and/or make a large error when measuring SMK. This result suggests that formal training programs for peanut graders should emphasize how to carefully measure SMK. The values of the between-groups and within-groups variances under the random effects model support this result.

### *Objective 5: Variability of Prices Introduced by the Use of Rounding of Grade Percentages*

Table 4.4 presents descriptive statistics of four pairs of pricing methods being compared to determine the effects of the use of rounding and cleaned sample weight on the variability of prices. Method A is the current U.S. peanut pricing method; that is,

**Table 4.3. Parameter Estimates of the Grade Factor Equations with Fixed and Random Effects Models**

| Parameter | Fixed Effects Estimate | Fixed Effects Standard Error | Fixed Effects t-ratio | Random Effects Estimate | Random Effects Standard Error | Random Effects t-ratio |
|---|---|---|---|---|---|---|
| *Sound Mature Kernels (SMK)* | | | | | | |
| Intercept | -99.1241 | 76.93 | -1.29 | -119.4897 | 76.77 | -1.56 |
| Cleaned Sample Weight | 0.8687 | 0.15 | 5.67 | 0.8751 | 0.15 | 5.72 |
| Weight Discrepancy | -0.6676 | 0.33 | -2.00 | -0.7296 | 0.33 | -2.21 |
| Between-Groups Variance | | | | 286.3887 | | |
| Within-Groups Variance | 26.0730 | | | 26.0712 | | |
| *Sound Splits (SS)* | | | | | | |
| Intercept | 100.2875 | 57.82 | 1.73 | 90.5113 | 57.73 | 1.57 |
| Cleaned Sample Weight | -0.1239 | 0.12 | -1.08 | -0.1222 | 0.12 | -1.06 |
| Weight Discrepancy | -0.0776 | 0.25 | -0.31 | -0.0961 | 0.25 | -0.39 |
| Between-Groups Variance | | | | 272.7718 | | |
| Within-Groups Variance | 14.7311 | | | 14.7302 | | |
| *Other Kernels (OK)* | | | | | | |
| Intercept | 17.6954 | 43.08 | 0.41 | 25.7835 | 42.97 | 0.60 |
| Cleaned Sample Weight | 0.0026 | 0.09 | 0.03 | -0.0035 | 0.09 | -0.04 |
| Weight Discrepancy | -0.1127 | 0.19 | -0.60 | -0.0670 | 0.18 | -0.37 |
| Between-Groups Variance | | | | 54.8105 | | |
| Within-Groups Variance | 8.1765 | | | 8.1760 | | |
| *Total Damage (TD)* | | | | | | |
| Intercept | 18.0022 | 14.75 | 1.22 | 17.5863 | 14.68 | 1.20 |
| Cleaned Sample Weight | -0.0301 | 0.03 | -1.03 | -0.0308 | 0.03 | -1.05 |
| Weight Discrepancy | 0.0609 | 0.06 | -0.95 | -0.0464 | 0.06 | -0.78 |
| Between-Groups Variance | | | | 1.3978 | | |
| Within-Groups Variance | 0.9587 | | | 0.9597 | | |
| *Hulls* | | | | | | |
| Intercept | -36.8609 | 26.77 | -1.38 | -14.0701 | 26.74 | -0.53 |
| Cleaned Sample Weight | 0.2827 | 0.05 | 5.31 | 0.2807 | 0.05 | 5.27 |
| Weight Discrepancy | -0.0812 | 0.12 | -0.70 | -0.0580 | 0.12 | -0.50 |
| Between-Groups Variance | | | | 94.5386 | | |
| Within-Groups Variance | 3.1565 | | | 3.1567 | | |

Note: Grade factors in grams are with no rounding since the weight discrepancy is a continuous variable. LOAD dummies for the fixed effects model are not printed.

prices are based on grade percentages with rounding/500g cleaned sample. Prices under method B are calculated based on grade percentages with no rounding/500g cleaned sample. Methods C versus D are similar to methods A versus B, but prices are calculated on grade percentages with rounding/actual cleaned sample and no rounding/actual cleaned sample.

The variability of prices due to rounding is measured by the standard deviation of the paired differences as shown in table 4.4. The variability of prices due to rounding for methods A versus B is 3.30 dollars/ton. Similarly, for methods C versus D is 3.35 dollars/ton. However, the variability of prices due to rounding and overweight cleaned samples is 4.28 dollars/ton for methods A versus C. In general, rounding does introduce noise in peanut pricing.

**Table 4.4. Descriptive Statistics of Four Pricing Methods Using Paired Data on Peanut Prices**

| Description | Mean | Standard Deviation | Minimum | Maximum |
|---|---|---|---|---|
| Method A vs. B | | | | |
| Prices A: Rounding/500g Cleaned Sample | 601.43 | 20.83 | 547.42 | 671.12 |
| Prices B: No Rounding/500g Cleaned Sample | 601.17 | 20.29 | 550.07 | 665.36 |
| Paired Differences | 0.25 | 3.30 | -6.44 | 7.98 |
| Mean Square Error | 10.94 | 13.00 | 0.00 | 63.70 |
| Number of Observations | 314 | | | |
| Method A vs. C | | | | |
| Prices A: Rounding/500g Cleaned Sample | 601.15 | 20.71 | 547.42 | 671.12 |
| Prices C: Rounding/Actual Cleaned Sample | 598.24 | 20.31 | 547.42 | 662.54 |
| Paired Differences | 2.90 | 4.28 | -8.58 | 16.36 |
| Mean Square Error | 26.67 | 42.28 | 0.00 | 267.72 |
| Number of Observations | 298 | | | |
| Method C vs. D | | | | |
| Prices C: Rounding/Actual Cleaned Sample | 598.81 | 20.74 | 547.42 | 663.34 |
| Prices D: No Rounding/Actual Cleaned Sample | 598.46 | 20.24 | 546.57 | 660.50 |
| Paired Differences | 0.36 | 3.35 | -7.03 | 8.31 |
| Mean Square Error | 11.34 | 13.18 | 0.00 | 69.04 |
| Number of Observations | 296 | | | |
| Method B vs. D | | | | |
| Prices B: No Rounding/500g Cleaned Sample | 601.72 | 20.43 | 550.07 | 665.36 |
| Prices D: No Rounding/Actual Cleaned Sample | 598.65 | 20.18 | 546.57 | 660.50 |
| Paired Differences | 3.07 | 2.30 | -0.76 | 7.51 |
| Mean Square Error | 14.69 | 14.88 | 0.00 | 56.36 |
| Number of Observations | 313 | | | |

Note: All prices related to observations requiring regrading have been excluded. Variability of prices is defined as the standard deviation of the paired differences. Prices are expressed in dollars.

The null hypothesis of averaged prices from methods A versus B being the same $(\mathrm{H}_0 : \mu_d = \mu_A - \mu_B = 0)$ was tested using the observed value of the t-statistic. The observed value is

$$t = \frac{\bar{D} - \mu_d}{\sigma_d / \sqrt{N}} = \frac{0.25 - 0}{3.30 / \sqrt{314}} = 1.36 .$$

Since 1.36 is less than 1.96; that is, the critical value for the two-tailed test of the t-statistic, with 313 degrees of freedom and a 5% significance level, we fail to reject the null hypothesis. Therefore, averaged prices under methods A versus B are the same. Similarly, the observed value of the t-statistic for the null hypothesis of average prices under methods C versus D being the same $(\mathrm{H}_0 : \mu_d = \mu_C - \mu_D = 0)$ is 1.83. Hence, we fail to reject the null hypothesis of average prices from methods C versus D being the same. The two pairs of pricing methods dealing with rounding (A versus B and C versus D) have no different mean responses. Therefore, rounding is not statistically significant at a 5% significance level.

***Objective 6: Estimation of the Probability of Regrading***

Table 4.5 shows the probability of regrading with and without rounding using the empirical p.d.f. method. Note that rounding does tend to increase the probability of regrading as cleaned sample sizes increase. However, the weakness of the nonparametric approach is that estimates are imprecise.

**Table 4.5. Probability of Regrading Based on the Empirical p.d.f. Method**

| Method of Grade Factor Determination | Size A (500.0g) | Size B (501.4g) | Size C (503.7g) | Size D (505.0g) |
|---|---|---|---|---|
| Rounding/500g Cleaned Sample | 0.0602 | 0.0241 | 0.0241 | 0.0723 |
| No Rounding/500g Cleaned Sample | 0.0482 | 0.0120 | 0.0361 | 0.0361 |
| Rounding/Actual Cleaned Sample | 0.0602 | 0.0482 | 0.1084 | 0.1446 |
| No Rounding/Actual Cleaned Sample | 0.0602 | 0.0241 | 0.0602 | 0.0723 |

Note: The probability of regrading is calculated by dividing the number of times regrading occurs (sum of grade percentages falls outside of the 99-101% range) by the total number of observations in each size (83). Note that with 100 observations and five regrades, the 95% confidence interval would be 0.0164-0.1129.

Table 4.6 provides the parameter estimates of the proposed normal-jump distribution of weight discrepancy in grams. All parameter estimates are statistically significant. The mean and the variance of the normal process associated with the weight lost as dust and kernels suggests that, on average, the grader is likely to lose 2.26g of the cleaned sample. The 95% confidence interval around this estimate, 0.32-4.20g, falls within the allowable tolerance (5g or 1% of the cleaned sample weight). The probability of losing 5g when no large error is made is only 0.0023. This result suggests that the range of the allowable tolerance is reasonable.

The jump process was assumed to be associated with infrequent equipment and human errors. The estimates of the jump process suggest that the probability of occurrence of a human or equipment error is 7.05%, with the size of these errors being $5.90 \pm 12.05g$. Figure 4.3 shows the normal-jump distribution of weight discrepancy in grams given a cleaned sample of 500g.

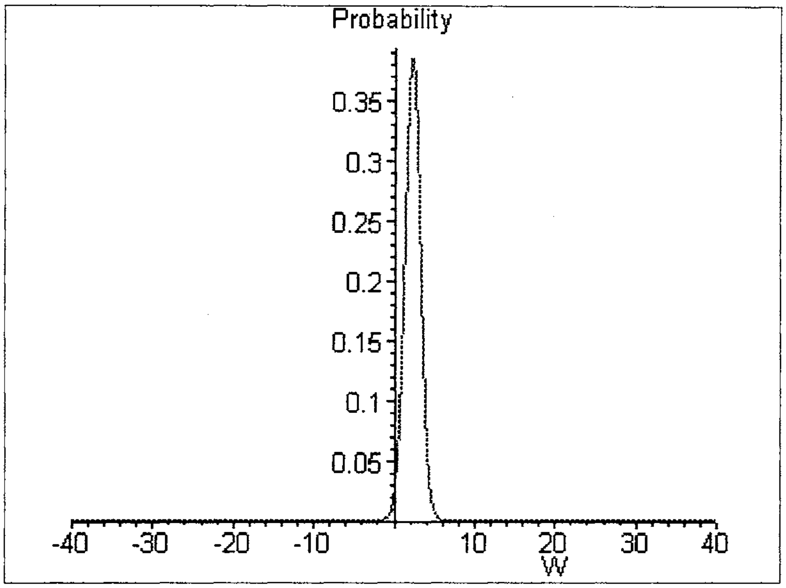


**Figure 4.3. The normal-jump distribution of weight discrepancy in grams for a cleaned sample of 500 grams**

**Table 4.6. Parameter Estimates of the Normal-Jump Distribution of Weight Discrepancy in Grams**

| Parameter | Symbol | Estimate | Standard Error | t-ratio |
|---|---|---|---|---|
| Mean of the Normal Process | $\alpha$ | 2.2630 | 0.0582 | 38.8690 |
| Variance of the Normal Process | $\sigma_N^2$ | 0.9390 | 0.0864 | 10.8640 |
| Jump Intensity | $\lambda$ | 0.0705 | 0.0188 | 3.7562 |
| Mean of the Poisson Jump | $\mu$ | 5.9020 | 2.6662 | 2.2136 |
| Variance of the Poisson Jump | $\sigma_J^2$ | 145.3000 | 58.6860 | 2.4760 |

Note: The log of the likelihood function is -578.0905. The number of observations is 332. No rounding is done.

The log-likelihood function value of the proposed normal-jump distribution is -578.0905. Also, the log-likelihood function values of a normal distribution with mean 2.68 and variance 14.61, a Gamma distribution with scale parameter 1 and shape parameter 3, and a Student t-distribution with four degrees of freedom, are -916.2976, -637.6075, and -1119.7020, respectively. For the nested test of a normal distribution, the observed value of the chi-square with three degrees of freedom, at a 5% significance level, is 7.81. So, the likelihood ratio tests lead to the rejection of a normal distribution. Likelihood odds ratios strongly favor the normal-jump distribution over the Gamma and Student t-distributions. Thus, the results show that the proposed normal-jump stochastic distribution seems to be the best model for estimating the probability of regrading without rounding.

The normal-jump distribution of weight discrepancy in grams was then used to estimate the probability of regrading without rounding $\Gamma_{NR}$ given a set of cleaned sample weights ranging from 495 to 505g. The multiple-dimension Monte Carlo integration provides the estimates for the probability of regrading with rounding.

Results in table 4.7 support the idea that rounding increases the probability of regrading and may provide the incentive for taking overweight cleaned samples. This is clearly depicted in Figure 4.4. Since the nonparametric approach did not exhibit nearly as clear of a pattern, this illustrates the importance of the greater efficiency provided by the parametric approach.

### *Objective 7: Differences in Average Grade Factors and Prices Given by Official and Private Graders in an Actual Situation*

Table 4.8 shows the method followed by a major U.S. peanut buyer to calculate the differences in grade factors and prices between purchased and regraded peanuts. The

**Table 4.7. Probability of Regrading Based on the Normal-Jump Distribution of Weight Discrepancy in Grams**

| Cleaned Sample Weight | Probability of Regrading with Rounding | Probability of Regrading without Rounding |
|---|---|---|
| 495 | 0.4948 | 0.9786 |
| 496 | 0.3843 | 0.8969 |
| 497 | 0.2781 | 0.6193 |
| 498 | 0.2008 | 0.2609 |
| 499 | 0.1277 | 0.0857 |
| 500 | 0.0877 | 0.0529 |
| 501 | 0.0634 | 0.0499 |
| 502 | 0.0533 | 0.0490 |
| 503 | 0.0520 | 0.0483 |
| 504 | 0.0685 | 0.0481 |
| 505 | 0.0965 | 0.0563 |

Note: The cleaned sample weight is expressed in grams.

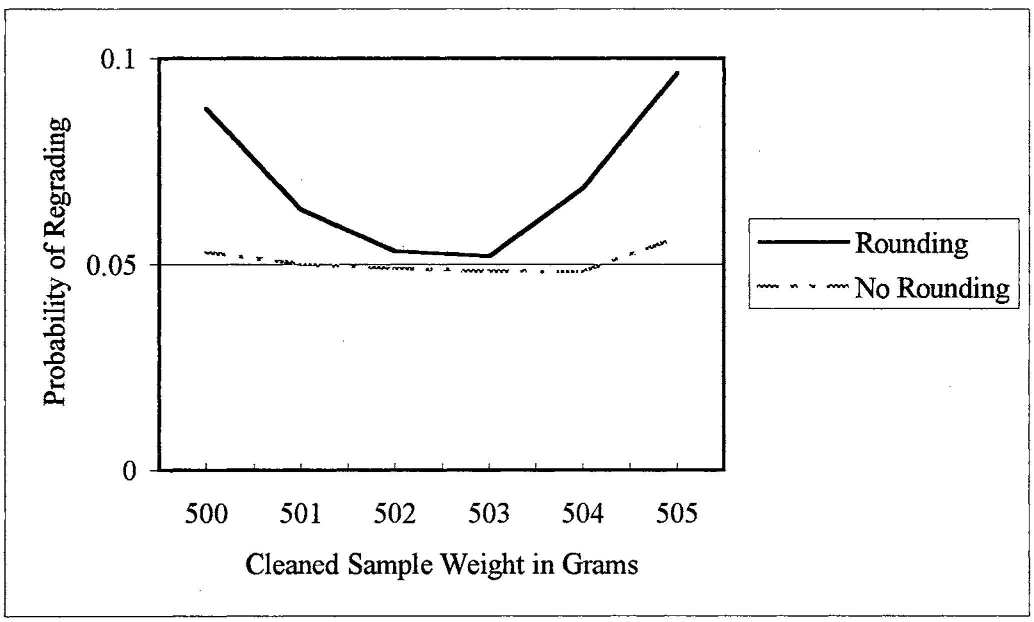


**Figure 4.4. Probability of regrading in the U.S. peanut industry**

results show that official graders do consistently overestimate sound mature kernels (SMK) but underestimate sound splits (SS) with respect to what private graders estimate. This could be explained, in part, by the absence of pressure on private graders. Figures

4.5, 4.6, and 4.7 show the differences in grade factors measured by official and private graders by peanut types. Note that, except for virginia peanuts, loose shelled kernels (LSK) increases due to drying out during shipment. Also, moisture did decrease.

Differences between average official and private grade factors can help determine the average actual cleaned sample used by official graders. The average cleaned sample weight used by official graders to begin the grade analysis for runner peanuts, the most common peanut type grown in Oklahoma, is

$$\text{Average Actual Cleaned Sample} = \frac{78.25\%}{78.10\%} x\ 500g = 500.96g\,.$$

This implies that, on average, official graders tend to take 0.96g more of runner peanuts in excess to the prescribed 500g. Similarly the average cleaned sample weights for virginia and spanish peanuts are 504.03 and 501.72g, respectively. This could provide some evidence that official graders may take overweight cleaned samples at the industry level. However, it is not possible to say what percentage of the bias is due to overweight cleaned samples.

The official grades, on average, yield prices \$6.20, \$5.79, and \$8.70 more per ton of virginia, runner, and spanish peanuts than the private grades. But, some of this difference is due to drying out during shipment. A more conservative estimate is, as before, to consider only the difference in total kernels. If this difference was solely sound mature kernels (SMK) then the overpayment to producers would be \$3.79, \$1.29, and \$2.15 for virginia, runner, and spanish peanuts. Using the smaller number for runner peanuts implies an overpayment to producers of \$1.65 million per year (1.28 million tons per year times \$1.29). As stated in the introduction, buyers will tend to recoup this loss by paying less for in-shell peanuts. The other factor that helps the buyers when prices are at the support price is that they can include up to 3% splits in what they sell.

**Table 4.8. Differences in Average Grade Factors and Prices per Ton in Dollars between Purchased and Regraded Peanuts by Type**

| | Buying Point | | Sheller | | Difference | |
|---|---|---|---|---|---|---|
| Grade Factors | Percent | Amount | Percent | Amount | Percent | Amount |
| ***Virginia Peanuts*** | | | | | | |
| Sound Mature Kernels (SMK) | 61.34 | 540.47 | 59.89 | 527.69 | -1.45 | -12.78 |
| Sound Splits (SS) | 7.45 | 65.64 | 8.22 | 72.43 | 0.77 | 6.79 |
| Total Sound Mature Kernels (TSMK) | 68.79 | 606.11 | 68.11 | 600.12 | -0.68 | -5.99 |
| Other Kernels (OK) | 1.72 | 2.41 | 1.77 | 2.48 | 0.05 | 0.07 |
| Total Damage (TD) | 0.76 | 0.00 | 0.82 | 0.00 | 0.06 | 0.00 |
| Total Kernels (Grade Factors) | 71.27 | 608.52 | 70.70 | 602.60 | -0.57 | -5.92 |
| Hulls | 28.73 | | 29.30 | | 0.57 | |
| Loose Shelled Kernels (LSK) | | 30.31 | | 29.27 | | -1.04 |
| Deductions (D) | | 3.40 | | 4.20 | | 0.80 |
| Total (LSK, D and Grade Factors) | 100.00 | 574.81 | 100.00 | 569.13 | 0.00 | -5.68 |
| Foreign Material (FM) | 5.68 | | 5.77 | | 0.09 | -0.52 |
| Moisture | 7.71 | | 7.33 | | -0.38 | |
| Loose Shelled Kernels (LSK) | 4.09 | | 3.95 | | -0.14 | |
| Total | | | | | | -6.20 |
| ***Runner Peanuts*** | | | | | | |
| Sound Mature Kernels (SMK) | 66.63 | 575.55 | 65.50 | 565.79 | -1.13 | -9.76 |
| Sound Splits (SS) | 8.34 | 72.04 | 9.53 | 82.32 | 1.19 | 10.28 |
| Total Sound Mature Kernels (TSMK) | 74.97 | 647.59 | 75.03 | 648.11 | 0.06 | 0.52 |
| Other Kernels (OK) | 3.01 | 4.21 | 2.80 | 3.92 | -0.21 | -0.29 |
| Total Damage (TD) | 0.27 | 0.00 | 0.27 | 0.00 | 0.00 | 0.00 |
| Total Kernels (Grade Factors) | 78.25 | 651.80 | 78.10 | 652.03 | -0.15 | 0.23 |
| Hulls | 21.75 | | 21.90 | | 0.15 | |
| Loose Shelled Kernels (LSK) | | 28.23 | | 31.34 | | 3.11 |
| Deductions (D) | | 4.20 | | 5.00 | | 0.80 |
| Total (LSK, D & Grade Factors) | 100.00 | 619.37 | 100.00 | 615.69 | | -3.68 |
| Foreign Material (FM) | 5.55 | | 5.89 | | 0.34 | -2.11 |
| Moisture | 8.04 | | 7.61 | | -0.43 | |
| Loose Shelled Kernels (LSK) | 3.90 | | 4.33 | | 0.43 | |
| Total | | | | | | -5.79 |
| ***Spanish Peanuts*** | | | | | | |
| Sound Mature Kernels (SMK) | 64.21 | 551.88 | 63.31 | 544.15 | -0.90 | -7.73 |
| Sound Splits (SS) | 5.20 | 44.69 | 5.84 | 50.19 | 0.64 | 5.50 |
| Total Sound Mature Kernels (TSMK) | 69.41 | 596.57 | 69.15 | 594.34 | -0.26 | -2.23 |
| Other Kernels (OK) | 3.26 | 4.56 | 3.25 | 4.55 | -0.01 | -0.01 |
| Total Damage (TD) | 0.18 | 0.00 | 0.20 | 0.00 | 0.02 | 0.00 |
| Total Kernels (Grade Factors) | 72.85 | 601.13 | 72.60 | 598.89 | -0.25 | -2.24 |
| Hulls | 27.14 | | 27.40 | | 0.26 | |
| Loose Shelled Kernels (LSK) | | 24.96 | | 27.20 | | 2.24 |
| Deductions (D) | | 1.80 | | 2.80 | | 1.00 |
| Total (LSK, D and Grade Factors) | 99.99 | 574.37 | 100.00 | 568.89 | 0.01 | -5.48 |
| Foreign Material (FM) | 5.78 | | 6.34 | | 0.56 | -3.22 |
| Moisture | 8.01 | | 7.55 | | -0.46 | |
| Loose Shelled Kernels (LSK) | 3.47 | | 3.78 | | 0.31 | |
| Total | | | | | | -8.70 |

Note: Includes purchases from all buying points for the year. Grade factors of purchased peanuts are based on truckloads at individual buying points. Regraded peanuts are based on semi-trailer loads either received at one of the firm's processing plants or warehouses. The sample for regrades is drawn within two days of the sample for the official grade.
Source: A major U.S. peanut buyer.

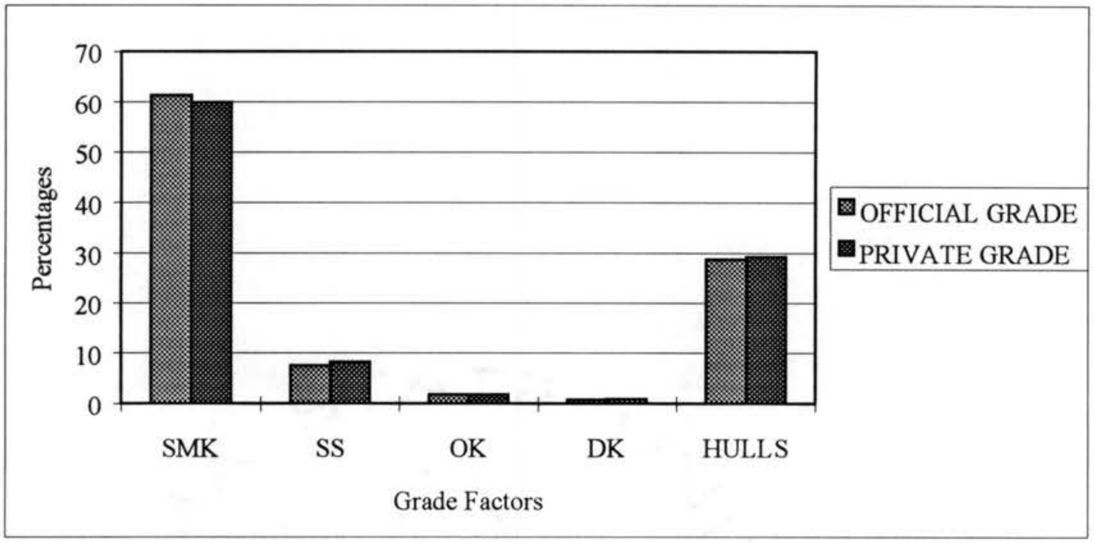


**Figure 4.5. Grade factors for virginia peanuts measured by official and private graders**

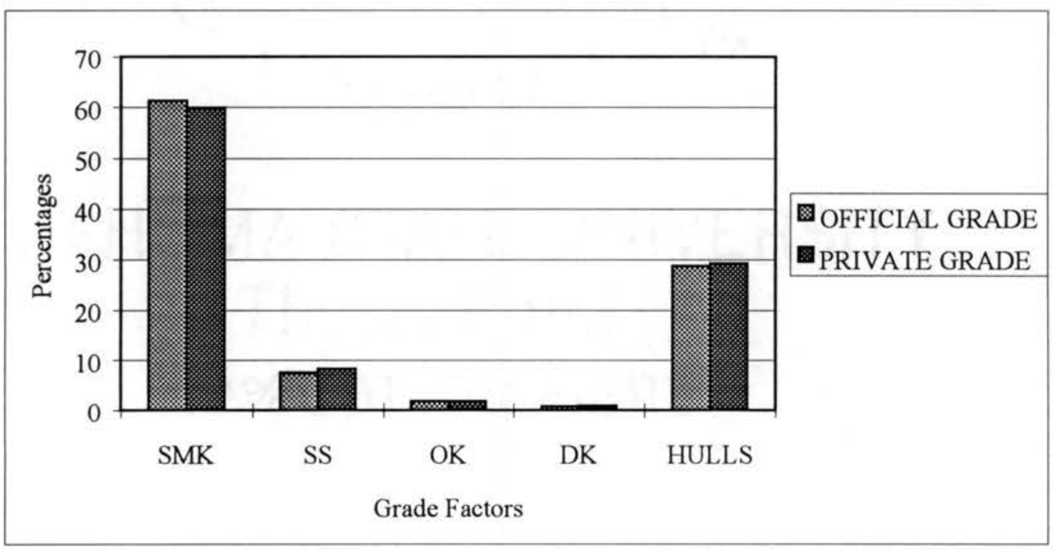


**Figure 4.6. Grade factors for runner peanuts measured by official and private graders**

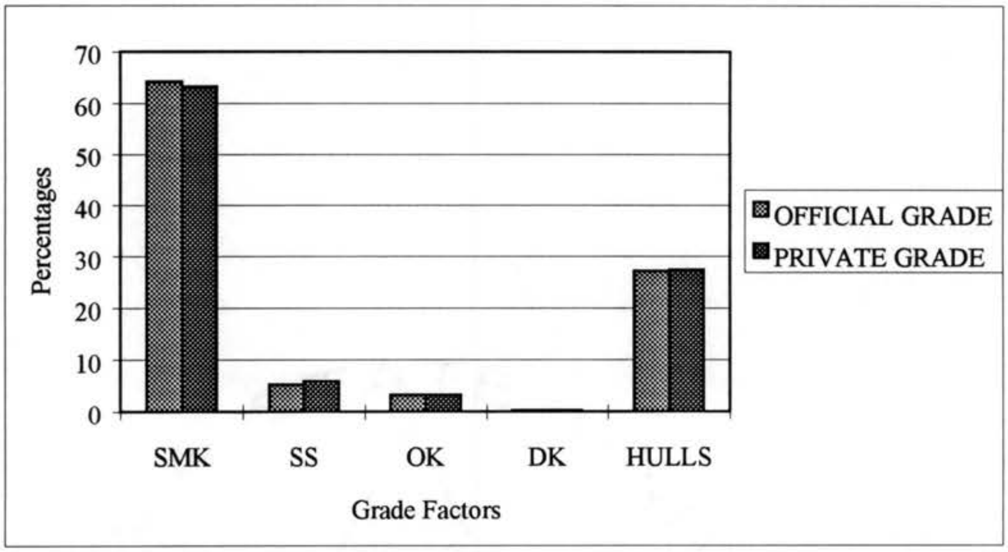


**Figure 4.7. Grade factors for spanish peanuts measured by official and private graders**

## CHAPTER V

## CONCLUSIONS

This study determined the effect of taking overweight cleaned samples and then measuring all grade factors as if the cleaned sample weight were exactly 500g, and the size of errors created by the use of rounding of grade percentages. These two problems have received no research attention in the economic literature. These problems are worthy of study because they affect the ability of the U.S. peanut grading system to clearly signal price/quality relationships. That is, these problems add noise to the market signal received by the producer and increase the risk faced by the buyer. Furthermore, policies to alleviate them may be adopted at a low cost.

In general, empirical results showed that taking overweight cleaned samples did result in higher prices. However, rounding did not affect, on average, expected prices or expected grade factors. Instead, rounding introduced noise and slightly increased the probability of regrading. We provided some evidence that these problems exist in the U.S. peanut industry.

A rigorous theoretical framework was developed to explain the grader's motivation to take overweight cleaned samples and to model the moral hazard problem deriving from the USDA/grader relationship. Two possible motivations were identified:

(1) the grader could simply avoid taking the time to get the cleaned sample weight precise, and (2) the grader would like to reduce the chances of regrading. However, in the absence of more specific information on the grader's personal, economic and psychological characteristics, we assumed that the grader was motivated to maximize a hybrid utility function that combines wage income, leisure, subjective or psychic income from internal or external sanctions, and effort. Previous moral hazard models have not considered both sociological and economic incentives. We proposed that subjective or psychic income could be included when modeling utility functions for seasonal, fixed-wage people such as the grader. Under this framework, effective norms and internal or external sanctions could help the USDA to indirectly induce the grader to apply high effort levels with less monitoring.

To attain this goal, a training-auditing strategy was analyzed under a moral hazard setting where the USDA was the principal and the grader was the agent. We proposed a model that included nonmonetary incentives such as a certain measure of pricing accuracy given by the expected pricing error in the USDA's objective function and the subjective or psychic income from internal or external sanctions in the grader's expected utility function. We assumed that the USDA implements a training program previous to the grading season to teach the grader how to grade more accurately. The auditing policy was based on taking a certain number of auditing samples and observing an imperfect statistical signal of effort proxied by the average absolute "buying-point" pricing error. We assumed that the USDA minimizes the expected pricing errors by following a training-auditing strategy that induces the grader to apply higher effort levels subject to its operating budget, the grader's expected utility level being no less than his or her reservation utility level and its inability to observe the grader's effort levels. We derived Kuhn-Tucker first-order conditions for the set of choice variables: wage payment, incentive payment, number of auditing samples and training. The solution to the optimization problem was to find an optimal training-auditing policy that could be useful to help understand USDA's policy choices.

In general, the optimal training-auditing policy may be influenced by the preferences of the grader, the density functions of the statistical signal of effort and the pricing error, the grader's effort choices, the price of auditing one lot, and the incentive payment scheme. Also, formal training programs for graders should aim at internalizing sanctions and thus creating consciousness and/or awareness of the problems deriving from taking overweight cleaned samples. The model conceives that the USDA may want to focus on sociological incentives rather than economic incentives because of the high cost of using economic incentives.

Because of the lack of data on the key variables used in this study such as the cleaned sample weight and the weight discrepancy in grams, there was a need to develop a designed experiment. The experiment used eighty-three 2,100g samples of peanuts taken from truckloads at their arrival at some grading stations across the state of Oklahoma during the 1996 harvest season. Each 2,100g sample was then divided into four 525g subsamples in order to have four different subsample sizes from the same sample. The cross-section data from this experiment were used to formally test the hypotheses regarding objectives 3 through 6 of this study.

The repeated-measures experimental design was used to estimate the effects of overweight cleaned samples and the weight discrepancy on expected prices and expected grade factors. The use of overweight cleaned samples in peanut grading was found to have a significantly positive relationship with the price per ton paid to producers when allowing for truckload-specific effects. There exists a one-to-one relationship between prices and cleaned sample weights. That is, a one percent increase in the cleaned sample weight results in a one percent increase in the price per ton paid to producers. Contrary to some grader beliefs, rounding did not remove the effect of larger cleaned sample weights, but introduced noise. Contrary to some buyer beliefs, rounding had no effect on mean prices. The impact of overweight cleaned samples on expected grade factors was only significant for sound mature kernels (SMK) and hulls. Again, rounding did not influence these results. The effect of weight discrepancy on expected grade factors was found to negatively influence SMK. This implied that most of the large errors were in measuring SMK.

The paired-differences experimental design was used to estimate the effects of rounding on the variability of prices. The variability of prices measured by the standard deviation of the paired differences for pricing methods based on grade percentages with rounding/500g cleaned sample (method A) and no rounding/500g cleaned sample (method B) was 3.30 dollars/ton. Similarly, pricing methods based on grade percentages with rounding/actual cleaned sample (method C) and no rounding/actual cleaned sample (method D) was 3.35 dollars/ton. However, the variability of prices introduced by the use of rounding and overweight cleaned samples was 4.28 dollars/ton when comparing pricing methods based on grade factors with rounding/500g cleaned sample (method A) and rounding/actual cleaned sample (method C). The tests of the hypotheses that the averaged prices for methods A versus B, and C versus D differed due to rounding were not statistically different at a 5% significance level.

Nonparametric and parametric methods were used to estimate the probability of regrading. Under the nonparametric approach the probability of regrading with and without rounding was estimated using the empirical p.d.f. method. Rounding did tend to increase the probability of regrading as cleaned samples sizes increased. However, the weakness of the nonparametric method was that estimates were imprecise. Under the parametric approach, we assumed the grader makes large infrequent errors. We proposed a new probability distribution called a normal-jump distribution of the weight discrepancy in grams to estimate the probability of regrading without rounding. All five parameter estimates of this distribution were statistically significant. The mean and the variance of the normal process associated with the cleaned sample weight lost as dust and kernels suggested that the grader was likely to lose 2.26g of the cleaned sample. The 95% confidence interval around this estimate, 0.32-4.20g, falls within the allowable tolerance (5g or 1% of the cleaned sample weight). The probability of losing 5g when no large error is made was only 0.0023. This results suggests that the range of the allowable tolerance is reasonable.

The jump process was assumed to be associated with infrequent equipment and human errors. The probability of occurrence of a large human or equipment error was 7.05%, with the size of these errors being $5.90 \pm 12.05g$. The results of the likelihood ratio tests led to rejection of normal, Gamma and Student t-distributions. The proposed normal-jump distribution seems to be the best model for estimating the probability of regrading without rounding.

A multiple-dimension Monte Carlo integration and the normal-jump distribution of the weight discrepancy in grams were used to estimate the probability of regrading with and without rounding, respectively. The results showed that rounding increases the probability of regrading and may provide the incentive to take overweight cleaned samples.

Data used to provide some evidence that official graders may be taking overweight cleaned samples came from the records kept by a major U.S. peanut buyer. The buyer followed its own methodology to calculate the differences in grade factors and prices between purchased and regraded peanuts. The results showed that official graders did consistently overestimate sound mature kernels (SMK) but underestimate sound splits (SS), with respect to what private graders obtained. We also provided some evidence that official graders might take overweight cleaned samples at the industry level. Differences between average official and private grade factors were used to estimate the average cleaned sample weights used by official graders to begin the grade analysis. The average cleaned sample weights were estimated as 504.03, 500.96, and 501.72g for virginia, runner, and spanish peanuts, respectively. However, it was not possible to say what percentage of the bias was due to overweight cleaned samples.

In short, we have documented that taking overweight cleaned samples overestimates the price of peanuts. However, rounding did not affect, on average, grade factors and prices, but did increase the probability of regrading. Our findings have some important implications for changes in policies and regulations aimed at refining the U.S. peanut grading system.

### *Implications for Government Policy*

This study suggests the following aspects to be considered if changing the current U.S. peanut grading system.

The first policy would be stop rounding to whole percentages. The current use of rounding directly introduces noise, increases costs due to more frequent regrading, and provides a major incentive for graders to use overweight samples. Grade factors could either be measured in grams or rounded to tenths rather than whole numbers. Now that we have computers and calculators, the extra computational effort would be small.

Second, the USDA should revise their training programs so that graders understand the consequences of taking overweight cleaned samples. As the new theoretical model showed, training can be sufficient to induce the desired action.

Both of these changes can be implemented at low cost and would help reduce the problem of overweight cleaned samples. It might first appear that reducing overweight cleaned samples would reduce the prices producers receive. If buyers are competitive, however, the overall price of peanuts would change in response to the change in measurement. Average producer prices should increase due to greater efficiency and lower risk of buyers.

Reducing overweight cleaned samples would reduce prices of quota peanuts. As margins increase for quota peanuts, margins for nonquota peanuts should be reduced. Buyers now have to charge high margins on nonquota peanuts in order to stay in business because of the artificially low margins on quota peanuts. Thus, the proposed policy changes should help the United States be more competitive in international markets.

### *Suggestions for Further Research*

In order to test the theoretical model, there is a need to study and generate data on the grader's personal characteristics using a multidisciplinary approach (say, a joint project developed by professionals from education, economics, human resource management and development, sociology, psychology, among other disciplines). For example, psychological techniques such as the life styles inventory as suggested by Cooke and Lafferty could be considered to determine the grader's behavior profile and his or her real motivations. A study to determine what income is really prevalent among graders (wage or psychic income, or both) can be done to provide more details on the grader's real motivations or perspectives. This study is a key element in the motivation strategy to be followed by the USDA.

The introduction of a third player, the Federal/State area supervisor, and collusion as discussed in Strausz, and the free-rider problem arising in teams as discussed in Holmstrom (1982) could be considered in refining the model presented in chapter 2. Also, the mathematical programming approach to moral hazard models as presented in Prescott could be considered. Additional restrictions and simpler functional forms to present a special case of the model presented in chapter 2 should be considered to attain the optimal shape of the choices variables.

A feasibility study of the new policy adoption or the impact of the adjustment is important. The primary tool used could be budgeting. Other constraints to adopting new policies, others than those identified before, could be explored by interviewing USDA officials, processors, exporters, politicians, among others.

Finally, empirical studies should consider alternative ways to test the hypotheses related to the effects of extension and training programs for and on both graders and the performance of the U.S. peanut grading system. The inclusion of qualitative data such as gender, experience, grading abilities, education level in the models used in this study can be considered in futures studies.

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# APPENDIXES

# APPENDIX A

# PEANUT GRADING CONTRACT

**CONTRACT TO PERFORM FRESH FRUIT AND VEGETABLE GRADING SERVICES**

Period of contract July 1, 1998 through June 30, 1999

This contract when accepted and activated, is made and entered into on the date below signed by the board, is by and between the Oklahoma State Board of Agriculture, hereinafter referred to as the Board, and SS# of Hereinafter referred to as the Second Party, an independent contractor licensed by the United States Department of Agriculture (USDA) to perform fresh fruit and vegetable grading services. It is mutually understood and agreed that in signing this contract no employment relationship is established between the State of Oklahoma or the Board and the Second Party. The parties hereto agree that the Second Party, an independent contractor, shall not be covered by the Board's workers compensation insurance, and neither the State of Oklahoma not the Board shall incur any liability for any claim or injury to the Second Party. The State or the Board shall incur no liability by any action or omission of the Second Party.

WITNESSETH:

WHEREAS the Board, in the interest of maintaining a well-functioning grading service for the farmer and the fresh fruit and vegetable industry, and

WHEREAS the Board not only has an interest but also the authority and responsibility to provide this valuable service in cooperation with USDA, and

WHEREAS the service required is of a seasonal Agricultural Nature, and

WHEREAS in view of the seasonal nature and the value of the fresh fruit and vegetable crop to Oklahoma farmers and Oklahomans in general, it is necessary to obtain the best possible qualified graders,

NOW, THEREFORE, in consideration of the covenants and agreements hereinafter set forth, it is mutually agreed between the parties hereto, as follows:

1. The Second Party hereby offers and agrees to provide fresh fruit and vegetable grading service in accordance with the terms, conditions and standards of the USDA license held by the Second Party.
2. The Second Party agrees to provide service during the hours designated for plant/buying point operation as determined by plant/buying point management.
3. The Second Party agrees to use only USDA approved equipment for grading services they are providing. They also agree to provide any necessary personal health and safety equipment such as ear plugs, dust masks, safety shoes, goggles, etc.
4. The Board agrees to compensate the Second Party based upon an invoice submitted biweekly by the Second Party based upon a fee schedule prescribed by the Board.
5. Both parties mutually agree that either party may cancel this agreement without prior notice.
6. In accepting this contract the Second Party agrees that books, records, documents, accounting, procedures, practices or any other items of the service provided by the Second Party relevant to this contract shall meet the standards of State and Federal laws and regulations and are subject to examination by USDA, by the Board, and the State Auditor and Inspector.
7. The Second Party is personally responsible for all Federal, State and local income, employment and other applicable taxes. Furthermore, the Second Party shall not have personal retirement contributions deducted from financial compensation.
8. The total amount of fees to be charged by the Second Party and the funds to be expended by the Board in the performance of this contract shall not exceed dollars, $ .
9. It is acknowledged that this contract will not take affect until such time that all parties have signed the contract, the Federal Supervisor (Licensing Authority) has verified and acknowledged that the Second Party will be licensed and the State Fruit and Vegetable Supervisor has verified that a defined service requirement exists.
10. The Second Party will provide the Board with a copy of the certificate of Insurance for Worker's compensation or a copy of the certificate of Non-coverage under the Worker's Compensation Act. This must be on file prior to beginning any contractual services or this contract becomes null and void.

Name of Second Party

Signature of Second Party Date

Accepted this day of 19

For the Board of Agriculture

# APPENDIX B

# DATA BASE

**Table A. Experimental Data on Peanut Grade Factors**

| Sample Code | Cleaned Sample Weight | Kernels Riding the Screen | Damaged Kernels | Sound Mature Kernels | Sound Splits | Total Sound Mature Kernels | Other Kernels |
|---|---|---|---|---|---|---|---|
| 1A-SP | 500.4 | 331.0 | 2.5 | 328.5 | 16.1 | 344.6 | 21.4 |
| 2A-SP | 500.6 | 328.5 | 0.2 | 328.3 | 16.4 | 344.7 | 24.1 |
| 3A-SP | 499.9 | 314.3 | 0.3 | 314.0 | 30.4 | 344.4 | 23.0 |
| 4A-SP | 500.1 | 316.9 | 1.5 | 315.4 | 30.3 | 345.7 | 18.2 |
| 5A-SP | 500.6 | 316.5 | 0.0 | 316.5 | 25.7 | 342.2 | 22.6 |
| 6A-SP | 499.8 | 311.2 | 1.6 | 309.6 | 33.3 | 342.9 | 20.3 |
| 7A-SP | 500.1 | 315.7 | 0.0 | 315.7 | 21.2 | 336.9 | 27.1 |
| 8A-SP | 500.1 | 302.7 | 0.1 | 302.6 | 34.5 | 337.1 | 26.4 |
| 9A-SP | 500.1 | 323.4 | 0.8 | 322.6 | 24.0 | 346.6 | 19.7 |
| 10A-SP | 500.1 | 318.0 | 0.5 | 317.5 | 22.8 | 340.3 | 26.2 |
| 11A-SP | 500.3 | 325.5 | 0.4 | 325.1 | 20.7 | 345.8 | 23.7 |
| 12A-SP | 500.3 | 331.9 | 3.0 | 328.9 | 15.2 | 344.1 | 17.9 |
| 13A-SP | 500.6 | 324.4 | 1.0 | 323.4 | 21.2 | 344.6 | 17.1 |
| 14A-SP | 499.5 | 310.4 | 0.4 | 310.0 | 24.5 | 334.5 | 31.2 |
| 15A-SP | 499.4 | 315.4 | 0.3 | 315.1 | 26.4 | 341.5 | 23.4 |
| 16A-SP | 499.9 | 313.4 | 0.4 | 313.0 | 23.9 | 336.9 | 22.5 |
| 17A-SP | 499.7 | 319.2 | 1.4 | 317.8 | 22.6 | 340.4 | 21.1 |
| 18A-SP | 500.4 | 310.8 | 0.5 | 310.3 | 24.0 | 334.3 | 27.1 |
| 19A-SP | 500.1 | 312.1 | 1.4 | 310.7 | 22.3 | 333.0 | 30.2 |
| 20A-SP | 500.1 | 323.1 | 0.9 | 322.2 | 21.7 | 343.9 | 22.9 |
| 21A-SP | 499.8 | 323.6 | 0.4 | 323.2 | 22.6 | 345.8 | 22.4 |
| 22A-SP | 500.0 | 318.5 | 0.9 | 317.6 | 22.5 | 340.1 | 25.1 |
| 23A-SP | 499.7 | 332.9 | 1.8 | 331.1 | 14.2 | 345.3 | 19.4 |
| 24A-SP | 500.3 | 311.6 | 3.1 | 308.5 | 35.7 | 344.2 | 18.8 |
| 25A-SP | 500.5 | 316.5 | 1.3 | 315.2 | 25.0 | 340.2 | 24.0 |
| 26A-SP | 500.4 | 330.1 | 0.0 | 330.1 | 21.6 | 351.7 | 15.7 |
| 27A-SP | 499.6 | 317.1 | 0.5 | 316.6 | 18.6 | 335.2 | 24.9 |
| 28A-SP | 499.8 | 313.1 | 0.3 | 312.8 | 27.0 | 339.8 | 27.2 |
| 29A-SP | 500.2 | 319.9 | 1.1 | 318.8 | 25.7 | 344.5 | 19.5 |
| 30A-SP | 500.0 | 327.7 | 0.2 | 327.5 | 25.2 | 352.7 | 14.1 |
| 31A-SP | 499.5 | 314.4 | 0.3 | 314.1 | 30.6 | 344.7 | 20.3 |
| 32A-SP | 499.7 | 334.5 | 1.4 | 333.1 | 24.5 | 357.6 | 12.8 |
| 33A-SP | 500.0 | 324.9 | 0.4 | 324.5 | 23.3 | 347.8 | 17.2 |
| 34A-SP | 500.0 | 315.0 | 0.3 | 314.7 | 10.7 | 325.4 | 41.2 |
| 35A-SP | 499.9 | 311.9 | 0.7 | 311.2 | 5.8 | 317.0 | 50.6 |
| 36A-SP | 499.9 | 315.9 | 0.0 | 315.9 | 26.9 | 342.8 | 23.0 |
| 37A-SP | 499.7 | 317.0 | 0.9 | 316.1 | 36.2 | 352.3 | 17.1 |
| 38A-SP | 500.0 | 314.6 | 0.8 | 313.8 | 26.2 | 340.0 | 25.2 |
| 39A-SP | 500.4 | 319.7 | 0.9 | 318.8 | 21.9 | 340.7 | 21.7 |

**Table A. Continued**

| Sample Code | Cleaned Sample Weight | Kernels Riding the Screen | Damaged Kernels | Sound Mature Kernels | Sound Splits | Total Sound Mature Kernels | Other Kernels |
|---|---|---|---|---|---|---|---|
| 40A-SP | 499.9 | 311.6 | 4.1 | 307.5 | 30.8 | 338.3 | 22.9 |
| 41A-SP | 500.2 | 322.1 | 2.3 | 319.8 | 12.4 | 332.2 | 30.8 |
| 42A-SP | 500.1 | 306.7 | 2.4 | 304.3 | 20.5 | 324.8 | 40.2 |
| 43A-SP | 500.0 | 321.7 | 2.0 | 319.7 | 22.6 | 342.3 | 18.4 |
| 44A-SP | 500.1 | 313.4 | 1.4 | 312.0 | 13.6 | 325.6 | 40.4 |
| 45A-SP | 500.2 | 311.9 | 1.2 | 310.7 | 10.0 | 320.7 | 17.0 |
| 46A-SP | 500.4 | 318.0 | 5.9 | 312.1 | 32.4 | 344.5 | 16.9 |
| 47A-SP | 500.1 | 316.7 | 2.1 | 314.6 | 20.3 | 334.9 | 23.9 |
| 48A-SP | 500.2 | 312.7 | 1.5 | 311.2 | 42.3 | 353.5 | 15.1 |
| 49A-SP | 500.2 | 309.4 | 0.9 | 308.5 | 22.7 | 331.2 | 23.2 |
| 50A-SP | 500.0 | 287.1 | 1.0 | 286.1 | 39.8 | 325.9 | 33.4 |
| 51A-SP | 500.0 | 323.9 | 1.2 | 322.7 | 26.2 | 348.9 | 16.5 |
| 52A-SP | 499.7 | 317.4 | 2.3 | 315.1 | 32.7 | 347.8 | 18.9 |
| 53A-SP | 499.4 | 320.5 | 0.8 | 319.7 | 20.2 | 339.9 | 21.6 |
| 54A-SP | 500.4 | 317.1 | 0.0 | 317.1 | 25.4 | 342.5 | 19.5 |
| 55A-SP | 500.1 | 321.1 | 0.0 | 321.1 | 30.5 | 351.6 | 15.9 |
| 56A-SP | 500.5 | 331.7 | 2.7 | 329.0 | 22.7 | 351.7 | 17.0 |
| 57A-SP | 499.9 | 298.6 | 0.6 | 298.0 | 27.9 | 325.9 | 34.4 |
| 58A-SP | 500.2 | 316.3 | 0.0 | 316.3 | 20.3 | 336.6 | 27.0 |
| 59A-R | 500.0 | 353.2 | 1.7 | 351.5 | 19.8 | 371.3 | 16.4 |
| 60A-R | 499.7 | 358.3 | 0.6 | 357.7 | 10.1 | 367.8 | 16.7 |
| 61A-R | 500.5 | 284.0 | 3.6 | 280.4 | 75.6 | 356.0 | 21.5 |
| 62A-R | 500.4 | 257.7 | 4.2 | 253.5 | 72.6 | 326.1 | 29.1 |
| 63A-R | 500.5 | 337.5 | 0.0 | 337.5 | 14.3 | 351.8 | 29.1 |
| 64A-R | 500.4 | 342.2 | 3.6 | 338.6 | 24.3 | 362.9 | 24.2 |
| 65A-R | 500.3 | 322.6 | 3.4 | 319.2 | 21.4 | 340.6 | 39.7 |
| 66A-R | 499.8 | 348.4 | 2.5 | 345.9 | 18.2 | 364.1 | 23.0 |
| 67A-R | 500.2 | 338.5 | 1.5 | 337.0 | 9.9 | 346.9 | 35.0 |
| 68A-R | 499.8 | 355.7 | 3.7 | 352.0 | 10.4 | 362.4 | 22.5 |
| 69A-R | 499.6 | 348.9 | 2.4 | 346.5 | 10.5 | 357.0 | 25.9 |
| 70A-R | 500.2 | 319.9 | 1.8 | 318.1 | 53.0 | 371.1 | 15.4 |
| 71A-R | 499.4 | 354.3 | 0.6 | 353.7 | 11.1 | 364.8 | 21.6 |
| 72A-R | 500.2 | 262.0 | 1.1 | 260.9 | 89.9 | 350.8 | 22.8 |
| 73A-R | 499.9 | 321.2 | 1.4 | 319.8 | 15.4 | 335.2 | 34.2 |
| 74A-R | 499.9 | 290.3 | 1.2 | 289.1 | 71.0 | 360.1 | 24.7 |
| 75A-R | 500.1 | 278.9 | 3.2 | 275.7 | 89.1 | 364.8 | 18.3 |
| 76A-R | 500.4 | 295.0 | 1.2 | 293.8 | 34.3 | 328.1 | 49.6 |
| 77A-R | 500.1 | 280.2 | 1.0 | 279.2 | 88.2 | 367.4 | 19.1 |
| 78A-R | 500.3 | 348.9 | 0.4 | 348.5 | 34.8 | 383.3 | 12.1 |
| 79A-R | 499.9 | 302.9 | 1.5 | 301.4 | 34.0 | 335.4 | 42.7 |

**Table A. Continued**

| Sample Code | Cleaned Sample Weight | Kernels Riding the Screen | Damaged Kernels | Sound Mature Kernels | Sound Splits | Total Sound Mature Kernels | Other Kernels |
|---|---|---|---|---|---|---|---|
| 80A-R | 499.8 | 319.2 | 1.2 | 318.0 | 59.1 | 377.1 | 14.4 |
| 81A-R | 500.3 | 304.6 | 3.2 | 301.4 | 46.2 | 347.6 | 30.2 |
| 82A-R | 499.4 | 286.2 | 3.8 | 282.4 | 70.9 | 353.3 | 25.9 |
| 83A-R | 499.8 | 345.6 | 2.2 | 343.4 | 34.0 | 377.4 | 15.6 |
| 1B-SP | 501.8 | 329.7 | 0.4 | 329.3 | 16.0 | 345.3 | 21.3 |
| 2B-SP | 501.9 | 316.0 | 0.0 | 316.0 | 28.0 | 344.0 | 22.0 |
| 3B-SP | 501.8 | 317.2 | 0.2 | 317.0 | 25.8 | 342.8 | 24.5 |
| 4B-SP | 501.9 | 321.6 | 1.5 | 320.1 | 24.0 | 344.1 | 17.3 |
| 5B-SP | 501.6 | 317.1 | 1.3 | 315.8 | 27.3 | 343.1 | 21.0 |
| 6B-SP | 501.7 | 318.5 | 0.5 | 318.0 | 21.1 | 339.1 | 25.3 |
| 7B-SP | 501.6 | 322.8 | 1.0 | 321.8 | 19.3 | 341.1 | 23.5 |
| 8B-SP | 501.3 | 318.0 | 0.0 | 318.0 | 23.4 | 341.4 | 24.4 |
| 9B-SP | 501.8 | 314.4 | 0.0 | 314.4 | 22.8 | 337.2 | 25.7 |
| 10B-SP | 501.6 | 322.6 | 0.4 | 322.2 | 19.5 | 341.7 | 25.0 |
| 11B-SP | 501.8 | 322.6 | 1.6 | 321.0 | 24.1 | 345.1 | 21.9 |
| 12B-SP | 501.5 | 320.8 | 0.6 | 320.2 | 19.8 | 340.0 | 26.1 |
| 13B-SP | 501.7 | 322.6 | 1.9 | 320.7 | 19.8 | 340.5 | 21.5 |
| 14B-SP | 501.8 | 314.6 | 1.9 | 312.7 | 24.4 | 337.1 | 26.0 |
| 15B-SP | 501.9 | 321.6 | 0.2 | 321.4 | 19.0 | 340.4 | 24.9 |
| 16B-SP | 501.8 | 329.4 | 0.0 | 329.4 | 23.7 | 353.1 | 15.0 |
| 17B-SP | 501.7 | 317.1 | 1.2 | 315.9 | 26.0 | 341.9 | 22.4 |
| 18B-SP | 501.6 | 318.7 | 0.0 | 318.7 | 20.6 | 339.3 | 26.8 |
| 19B-SP | 501.9 | 318.7 | 0.2 | 318.5 | 21.5 | 340.0 | 25.4 |
| 20B-SP | 501.5 | 315.3 | 1.1 | 314.2 | 24.4 | 338.6 | 27.8 |
| 21B-SP | 501.6 | 318.6 | 1.4 | 317.2 | 25.3 | 342.5 | 17.7 |
| 22B-SP | 501.5 | 321.4 | 0.5 | 320.9 | 24.7 | 345.6 | 24.3 |
| 23B-SP | 501.9 | 334.2 | 0.7 | 333.5 | 13.0 | 346.5 | 22.5 |
| 24B-SP | 501.6 | 307.4 | 1.7 | 305.7 | 37.2 | 342.9 | 23.2 |
| 25B-SP | 501.5 | 324.9 | 0.5 | 324.4 | 20.7 | 345.1 | 21.7 |
| 26B-SP | 501.6 | 322.0 | 0.6 | 321.4 | 24.1 | 345.5 | 21.5 |
| 27B-SP | 501.2 | 321.4 | 0.0 | 321.4 | 27.4 | 348.8 | 17.9 |
| 28B-SP | 501.5 | 320.6 | 1.9 | 318.7 | 20.0 | 338.7 | 25.1 |
| 29B-SP | 502.0 | 313.3 | 0.9 | 312.4 | 27.4 | 339.8 | 26.1 |
| 30B-SP | 501.5 | 317.9 | 0.8 | 317.1 | 30.1 | 347.2 | 16.6 |
| 31B-SP | 501.7 | 313.8 | 0.0 | 313.8 | 31.0 | 344.8 | 23.3 |
| 32B-SP | 501.5 | 329.2 | 0.3 | 328.9 | 20.9 | 349.8 | 15.3 |
| 33B-SP | 501.7 | 326.6 | 0.0 | 326.6 | 18.9 | 345.5 | 19.8 |
| 34B-SP | 501.9 | 320.3 | 1.1 | 319.2 | 15.6 | 334.8 | 31.5 |
| 35B-SP | 501.9 | 305.3 | 1.2 | 304.1 | 10.4 | 314.5 | 50.7 |
| 36B-SP | 501.5 | 321.9 | 0.0 | 321.9 | 24.4 | 346.3 | 19.1 |

**Table A. Continued**

| Cleaned Code | Cleaned Sample Weight | Kernels Riding the Screen | Damaged Kernels | Sound Mature Kernels | Sound Splits | Total Sound Mature Kernels | Other Kernels |
|---|---|---|---|---|---|---|---|
| 37B-SP | 502.0 | 315.2 | 2.2 | 313.0 | 30.4 | 343.4 | 23.1 |
| 38B-SP | 501.5 | 323.5 | 0.6 | 322.9 | 25.1 | 348.0 | 19.1 |
| 39B-SP | 501.7 | 316.0 | 1.0 | 315.0 | 27.6 | 342.6 | 21.1 |
| 40B-SP | 501.4 | 322.5 | 2.3 | 320.2 | 18.2 | 338.4 | 23.3 |
| 41B-SP | 501.8 | 316.6 | 2.9 | 313.7 | 21.5 | 335.2 | 28.3 |
| 42B-SP | 501.4 | 305.4 | 2.4 | 303.0 | 18.9 | 321.9 | 41.4 |
| 43B-SP | 501.6 | 322.4 | 0.5 | 321.9 | 27.0 | 348.9 | 13.7 |
| 44B-SP | 501.9 | 315.8 | 0.3 | 315.5 | 10.1 | 325.6 | 42.3 |
| 45B-SP | 501.6 | 304.4 | 1.0 | 303.4 | 12.8 | 316.2 | 16.2 |
| 46B-SP | 501.9 | 301.8 | 1.6 | 300.2 | 40.5 | 340.7 | 25.0 |
| 47B-SP | 501.7 | 319.9 | 1.3 | 318.6 | 19.2 | 337.8 | 24.8 |
| 48B-SP | 502.0 | 325.1 | 0.6 | 324.5 | 28.2 | 352.7 | 17.9 |
| 49B-SP | 501.8 | 308.3 | 2.1 | 306.2 | 22.5 | 328.7 | 20.5 |
| 50B-SP | 501.8 | 277.7 | 0.7 | 277.0 | 47.2 | 324.2 | 33.5 |
| 51B-SP | 501.6 | 318.0 | 1.2 | 316.8 | 26.2 | 343.0 | 18.1 |
| 52B-SP | 502.1 | 330.0 | 1.6 | 328.4 | 23.8 | 352.2 | 18.0 |
| 53B-SP | 501.6 | 319.2 | 1.1 | 318.1 | 23.6 | 341.7 | 20.4 |
| 54B-SP | 501.8 | 320.8 | 1.8 | 319.0 | 21.4 | 340.4 | 25.9 |
| 55B-SP | 501.8 | 319.8 | 0.8 | 319.0 | 29.7 | 348.7 | 16.0 |
| 56B-SP | 501.8 | 337.2 | 2.5 | 334.7 | 18.6 | 353.3 | 17.2 |
| 57B-SP | 501.5 | 287.5 | 2.6 | 284.9 | 38.6 | 323.5 | 34.5 |
| 58B-SP | 501.6 | 322.4 | 0.1 | 322.3 | 20.4 | 342.7 | 21.9 |
| 59B-R | 502.0 | 361.3 | 2.6 | 358.7 | 14.6 | 373.3 | 13.8 |
| 60B-R | 502.1 | 342.9 | 1.5 | 341.4 | 21.3 | 362.7 | 22.9 |
| 61B-R | 501.5 | 283.5 | 1.2 | 282.3 | 77.5 | 359.8 | 25.3 |
| 62B-R | 501.7 | 269.5 | 2.5 | 267.0 | 63.9 | 330.9 | 26.8 |
| 63B-R | 501.9 | 337.4 | 1.0 | 336.4 | 18.1 | 354.5 | 29.0 |
| 64B-R | 501.9 | 336.4 | 2.1 | 334.3 | 22.9 | 357.2 | 27.7 |
| 65B-R | 501.7 | 323.5 | 2.3 | 321.2 | 21.7 | 342.9 | 39.8 |
| 66B-R | 501.7 | 354.0 | 2.1 | 351.9 | 14.3 | 366.2 | 18.3 |
| 67B-R | 501.7 | 333.3 | 2.0 | 331.3 | 16.6 | 347.9 | 31.7 |
| 68B-R | 502.0 | 348.6 | 2.7 | 345.9 | 14.7 | 360.6 | 23.3 |
| 69B-R | 501.7 | 346.8 | 2.7 | 344.1 | 15.9 | 360.0 | 22.2 |
| 70B-R | 501.8 | 317.4 | 3.4 | 314.0 | 52.4 | 366.4 | 16.8 |
| 71B-R | 501.7 | 366.7 | 1.6 | 365.1 | 7.6 | 372.7 | 18.5 |
| 72B-R | 501.4 | 268.6 | 1.1 | 267.5 | 88.4 | 355.9 | 25.0 |
| 73B-R | 501.6 | 314.7 | 1.3 | 313.4 | 18.1 | 331.5 | 38.2 |
| 74B-R | 502.0 | 298.4 | 2.0 | 296.4 | 74.7 | 371.1 | 16.2 |
| 75B-R | 501.5 | 273.9 | 2.3 | 271.6 | 85.2 | 356.8 | 25.8 |
| 76B-R | 501.6 | 312.4 | 3.0 | 309.4 | 25.9 | 335.3 | 41.0 |

**Table A. Continued**

| Sample Code | Cleaned Sample Weight | Kernels Riding the Screen | Damaged Kernels | Sound Mature Kernels | Sound Splits | Total Sound Mature Kernels | Other Kernels |
|---|---|---|---|---|---|---|---|
| 77B-R | 501.8 | 301.0 | 1.6 | 299.4 | 70.0 | 369.4 | 13.4 |
| 78B-R | 501.6 | 350.1 | 0.7 | 349.4 | 30.5 | 379.9 | 15.8 |
| 79B-R | 502.0 | 304.1 | 2.5 | 301.6 | 39.3 | 340.9 | 38.4 |
| 80B-R | 501.8 | 326.6 | 0.4 | 326.2 | 60.3 | 386.5 | 9.0 |
| 81B-R | 501.7 | 313.1 | 3.8 | 309.3 | 40.1 | 349.4 | 30.0 |
| 82B-R | 501.9 | 294.8 | 3.3 | 291.5 | 60.9 | 352.4 | 28.7 |
| 83B-R | 501.8 | 327.3 | 3.8 | 323.5 | 45.7 | 369.2 | 17.7 |
| 1C-SP | 503.6 | 341.9 | 1.1 | 340.8 | 12.3 | 353.1 | 17.0 |
| 2C-SP | 503.8 | 323.0 | 0.6 | 322.4 | 23.7 | 346.1 | 21.6 |
| 3C-SP | 503.4 | 316.1 | 1.1 | 315.0 | 29.8 | 344.8 | 17.8 |
| 4C-SP | 503.7 | 322.7 | 1.9 | 320.8 | 25.4 | 346.2 | 17.2 |
| 5C-SP | 503.3 | 322.2 | 0.0 | 322.2 | 23.0 | 345.2 | 20.3 |
| 6C-SP | 503.7 | 321.7 | 0.0 | 321.7 | 26.3 | 348.0 | 19.8 |
| 7C-SP | 503.1 | 310.5 | 0.5 | 310.0 | 25.5 | 335.5 | 28.8 |
| 8C-SP | 503.5 | 314.8 | 0.0 | 314.8 | 29.5 | 344.3 | 22.2 |
| 9C-SP | 503.3 | 329.3 | 0.0 | 329.3 | 20.9 | 350.2 | 21.7 |
| 10C-SP | 503.7 | 311.4 | 0.5 | 310.9 | 27.9 | 338.8 | 27.0 |
| 11C-SP | 503.6 | 328.2 | 1.0 | 327.2 | 21.5 | 348.7 | 19.4 |
| 12C-SP | 503.3 | 330.1 | 0.5 | 329.6 | 17.5 | 347.1 | 20.5 |
| 13C-SP | 503.7 | 322.9 | 2.9 | 320.0 | 20.7 | 340.7 | 22.5 |
| 14C-SP | 503.2 | 315.2 | 1.7 | 313.5 | 29.8 | 343.3 | 23.7 |
| 15C-SP | 503.3 | 325.3 | 1.3 | 324.0 | 25.7 | 349.7 | 18.4 |
| 16C-SP | 503.8 | 323.3 | 0.3 | 323.0 | 31.2 | 354.2 | 19.1 |
| 17C-SP | 503.8 | 323.0 | 1.3 | 321.7 | 23.2 | 344.9 | 20.2 |
| 18C-SP | 503.7 | 311.9 | 0.9 | 311.0 | 27.3 | 338.3 | 28.6 |
| 19C-SP | 503.6 | 315.5 | 0.2 | 315.3 | 20.8 | 336.1 | 29.0 |
| 20C-SP | 503.3 | 326.4 | 0.0 | 326.4 | 20.0 | 346.4 | 22.0 |
| 21C-SP | 503.5 | 316.9 | 1.3 | 315.6 | 25.9 | 341.5 | 24.6 |
| 22C-SP | 503.4 | 326.1 | 1.1 | 325.0 | 24.2 | 349.2 | 20.1 |
| 23C-SP | 503.8 | 337.5 | 1.0 | 336.5 | 8.2 | 344.7 | 23.8 |
| 24C-SP | 503.7 | 317.3 | 2.9 | 314.4 | 27.3 | 341.7 | 19.6 |
| 25C-SP | 503.8 | 324.5 | 0.0 | 324.5 | 20.8 | 345.3 | 23.6 |
| 26C-SP | 503.2 | 314.7 | 1.7 | 313.0 | 26.6 | 339.6 | 21.7 |
| 27C-SP | 503.5 | 323.5 | 0.7 | 322.8 | 26.4 | 349.2 | 17.0 |
| 28C-SP | 503.1 | 311.2 | 1.0 | 310.2 | 29.0 | 339.2 | 25.2 |
| 29C-SP | 503.1 | 312.0 | 0.7 | 311.3 | 29.8 | 341.1 | 24.2 |
| 30C-SP | 503.7 | 320.1 | 0.9 | 319.2 | 22.6 | 341.8 | 25.0 |
| 31C-SP | 503.8 | 315.7 | 0.4 | 315.3 | 30.1 | 345.4 | 22.4 |
| 32C-SP | 503.4 | 331.8 | 0.8 | 331.0 | 20.5 | 351.5 | 15.6 |
| 33C-SP | 503.3 | 324.3 | 0.5 | 323.8 | 24.8 | 348.6 | 18.2 |

**Table A. Continued**

| Sample Code | Cleaned Sample Weight | Kernels Riding the Screen | Damaged Kernels | Sound Mature Kernels | Sound Splits | Total Sound Mature Kernels | Other Kernels |
|---|---|---|---|---|---|---|---|
| 34C-SP | 503.2 | 325.8 | 0.0 | 325.8 | 18.9 | 344.7 | 26.5 |
| 35C-SP | 503.2 | 307.3 | 0.5 | 306.8 | 4.4 | 311.2 | 57.1 |
| 36C-SP | 503.5 | 318.9 | 0.4 | 318.5 | 30.1 | 348.6 | 16.7 |
| 37C-SP | 503.7 | 319.7 | 1.3 | 318.4 | 33.9 | 352.3 | 19.3 |
| 38C-SP | 503.4 | 299.8 | 1.9 | 297.9 | 26.0 | 323.9 | 20.5 |
| 39C-SP | 503.3 | 323.0 | 0.0 | 323.0 | 22.3 | 345.3 | 20.8 |
| 40C-SP | 503.3 | 320.4 | 0.8 | 319.6 | 26.8 | 346.4 | 20.0 |
| 41C-SP | 503.4 | 317.4 | 2.5 | 314.9 | 19.7 | 334.6 | 29.4 |
| 42C-SP | 503.2 | 307.6 | 1.6 | 306.0 | 18.7 | 324.7 | 38.9 |
| 43C-SP | 503.2 | 331.7 | 0.7 | 331.0 | 20.1 | 351.1 | 13.8 |
| 44C-SP | 503.8 | 316.9 | 2.1 | 314.8 | 9.4 | 324.2 | 41.8 |
| 45C-SP | 503.6 | 315.0 | 0.7 | 314.3 | 9.1 | 323.4 | 15.1 |
| 46C-SP | 503.3 | 314.9 | 1.9 | 313.0 | 29.3 | 342.3 | 25.6 |
| 47C-SP | 503.2 | 321.4 | 4.1 | 317.3 | 18.2 | 335.5 | 22.2 |
| 48C-SP | 503.3 | 316.4 | 2.4 | 314.0 | 30.7 | 344.7 | 23.8 |
| 49C-SP | 503.6 | 312.8 | 1.2 | 311.6 | 22.4 | 334.0 | 19.4 |
| 50C-SP | 503.6 | 288.8 | 0.8 | 288.0 | 40.1 | 328.1 | 33.1 |
| 51C-SP | 503.4 | 328.6 | 0.8 | 327.8 | 22.6 | 350.4 | 15.5 |
| 52C-SP | 504.1 | 331.2 | 1.1 | 330.1 | 27.1 | 357.2 | 12.6 |
| 53C-SP | 503.6 | 317.5 | 0.6 | 316.9 | 24.9 | 341.8 | 23.3 |
| 54C-SP | 503.6 | 325.8 | 1.3 | 324.5 | 24.6 | 349.1 | 21.1 |
| 55C-SP | 503.5 | 326.6 | 1.3 | 325.3 | 28.5 | 353.8 | 16.2 |
| 56C-SP | 503.8 | 338.8 | 1.6 | 337.2 | 20.0 | 357.2 | 14.7 |
| 57C-SP | 503.4 | 296.1 | 1.5 | 294.6 | 37.0 | 331.6 | 30.5 |
| 58C-SP | 503.3 | 318.6 | 0.0 | 318.6 | 24.9 | 343.5 | 23.0 |
| 59C-R | 503.1 | 366.6 | 1.6 | 365.0 | 7.8 | 372.8 | 18.0 |
| 60C-R | 503.7 | 346.6 | 0.0 | 346.6 | 17.8 | 364.4 | 24.1 |
| 61C-R | 503.3 | 282.1 | 3.9 | 278.2 | 78.4 | 356.6 | 21.0 |
| 62C-R | 503.6 | 274.5 | 1.8 | 272.7 | 60.3 | 333.0 | 34.3 |
| 63C-R | 503.5 | 342.7 | 0.6 | 342.1 | 14.4 | 356.5 | 29.8 |
| 64C-R | 503.2 | 345.2 | 0.7 | 344.5 | 19.5 | 364.0 | 21.5 |
| 65C-R | 503.3 | 330.8 | 2.3 | 328.5 | 21.5 | 350.0 | 32.1 |
| 66C-R | 503.6 | 357.9 | 0.0 | 357.9 | 11.3 | 369.2 | 20.4 |
| 67C-R | 503.2 | 339.0 | 2.0 | 337.0 | 15.6 | 352.6 | 35.4 |
| 68C-R | 503.6 | 344.7 | 3.8 | 340.9 | 14.0 | 354.9 | 28.3 |
| 69C-R | 503.5 | 355.5 | 1.3 | 354.2 | 11.6 | 365.8 | 22.5 |
| 70C-R | 503.8 | 319.8 | 3.4 | 316.4 | 57.8 | 374.2 | 13.8 |
| 71C-R | 503.4 | 355.8 | 1.8 | 354.0 | 10.2 | 364.2 | 20.3 |
| 72C-R | 503.9 | 274.0 | 4.0 | 270.0 | 74.5 | 344.5 | 25.9 |
| 73C-R | 503.3 | 317.1 | 2.9 | 314.2 | 15.1 | 329.3 | 41.4 |

**Table A. Continued**

| Sample Code | Cleaned Sample Weight | Kernels Riding the Screen | Damaged Kernels | Sound Mature Kernels | Sound Splits | Total Sound Mature Kernels | Other Kernels |
|---|---|---|---|---|---|---|---|
| 74C-R | 503.6 | 300.3 | 2.3 | 298.0 | 75.4 | 373.4 | 15.0 |
| 75C-R | 503.4 | 282.1 | 2.8 | 279.3 | 86.6 | 365.9 | 13.3 |
| 76C-R | 503.5 | 300.9 | 3.6 | 297.3 | 38.5 | 335.8 | 41.5 |
| 77C-R | 503.6 | 305.8 | 1.9 | 303.9 | 65.8 | 369.7 | 16.3 |
| 78C-R | 503.7 | 355.8 | 1.8 | 354.0 | 32.8 | 386.8 | 12.8 |
| 79C-R | 503.3 | 307.5 | 1.9 | 305.6 | 28.6 | 334.2 | 47.3 |
| 80C-R | 503.6 | 320.8 | 1.6 | 319.2 | 57.6 | 376.8 | 16.3 |
| 81C-R | 504.3 | 314.6 | 3.3 | 311.3 | 39.5 | 350.8 | 30.4 |
| 82C-R | 504.1 | 303.4 | 2.5 | 300.9 | 58.1 | 359.0 | 24.8 |
| 83C-R | 503.6 | 339.2 | 1.6 | 337.6 | 39.3 | 376.9 | 18.9 |
| 1D-SP | 505.1 | 334.6 | 0.8 | 333.8 | 18.5 | 352.3 | 18.2 |
| 2D-SP | 505.2 | 316.0 | 0.4 | 315.6 | 25.1 | 340.7 | 25.8 |
| 3D-SP | 504.8 | 319.2 | 0.4 | 318.8 | 31.8 | 350.6 | 19.6 |
| 4D-SP | 505.2 | 324.1 | 0.6 | 323.5 | 31.2 | 354.7 | 13.4 |
| 5D-SP | 505.0 | 325.3 | 0.5 | 324.8 | 26.9 | 351.7 | 19.3 |
| 6D-SP | 505.6 | 314.2 | 1.0 | 313.2 | 31.8 | 345.0 | 24.4 |
| 7D-SP | 504.9 | 320.8 | 0.5 | 320.3 | 19.5 | 339.8 | 29.2 |
| 8D-SP | 505.0 | 319.9 | 1.5 | 318.4 | 28.2 | 346.6 | 21.4 |
| 9D-SP | 505.0 | 316.8 | 0.7 | 316.1 | 28.6 | 344.7 | 23.6 |
| 10D-SP | 505.2 | 320.7 | 0.0 | 320.7 | 22.0 | 342.7 | 23.5 |
| 11D-SP | 505.2 | 321.5 | 1.0 | 320.5 | 21.6 | 342.1 | 25.2 |
| 12D-SP | 504.9 | 332.1 | 1.8 | 330.3 | 16.7 | 347.0 | 21.8 |
| 13D-SP | 505.4 | 324.3 | 1.9 | 322.4 | 19.4 | 341.8 | 24.6 |
| 14D-SP | 505.1 | 328.2 | 0.2 | 328.0 | 19.3 | 347.3 | 20.7 |
| 15D-SP | 505.0 | 321.0 | 1.0 | 320.0 | 23.8 | 343.8 | 23.5 |
| 16D-SP | 504.6 | 317.9 | 1.4 | 316.5 | 22.7 | 339.2 | 26.8 |
| 17D-SP | 505.1 | 320.8 | 1.6 | 319.2 | 27.6 | 346.8 | 17.8 |
| 18D-SP | 504.7 | 313.6 | 1.5 | 312.1 | 49.9 | 362.0 | 29.7 |
| 19D-SP | 505.0 | 325.3 | 0.8 | 324.5 | 18.2 | 342.7 | 25.0 |
| 20D-SP | 505.5 | 316.9 | 1.6 | 315.3 | 26.2 | 341.5 | 23.1 |
| 21D-SP | 504.9 | 325.8 | 0.3 | 325.5 | 23.0 | 348.5 | 23.1 |
| 22D-SP | 505.0 | 320.8 | 0.0 | 320.8 | 25.9 | 346.7 | 20.1 |
| 23D-SP | 505.2 | 325.7 | 0.0 | 325.7 | 22.1 | 347.8 | 24.4 |
| 24D-SP | 505.0 | 313.7 | 2.5 | 311.2 | 31.5 | 342.7 | 23.6 |
| 25D-SP | 505.1 | 327.8 | 0.8 | 327.0 | 21.8 | 348.8 | 20.4 |
| 26D-SP | 505.1 | 321.5 | 0.9 | 320.6 | 21.8 | 342.4 | 23.6 |
| 27D-SP | 504.9 | 321.0 | 0.4 | 320.6 | 25.4 | 346.0 | 22.2 |
| 28D-SP | 505.1 | 315.1 | 0.2 | 314.9 | 27.4 | 342.3 | 27.5 |
| 29D-SP | 505.1 | 329.4 | 0.7 | 328.7 | 21.3 | 350.0 | 17.1 |
| 30D-SP | 505.3 | 329.4 | 1.5 | 327.9 | 28.1 | 356.0 | 13.8 |

**Table A. Continued**

| Sample Code | Cleaned Sample Weight | Kernels Riding the Screen | Damaged Kernels | Sound Mature Kernels | Sound Splits | Total Sound Mature Kernels | Other Kernels |
|---|---|---|---|---|---|---|---|
| 31D-SP | 505.0 | 324.3 | 0.4 | 323.9 | 28.5 | 352.4 | 17.2 |
| 32D-SP | 505.2 | 329.0 | 1.8 | 327.2 | 27.8 | 355.0 | 14.4 |
| 33D-SP | 505.3 | 320.8 | 0.0 | 320.8 | 25.7 | 346.5 | 17.7 |
| 34D-SP | 505.1 | 317.6 | 0.5 | 317.1 | 14.8 | 331.9 | 36.8 |
| 35D-SP | 504.9 | 311.1 | 0.7 | 310.4 | 5.8 | 316.2 | 53.1 |
| 36D-SP | 505.2 | 317.8 | 0.0 | 317.8 | 27.9 | 345.7 | 22.1 |
| 37D-SP | 505.2 | 319.2 | 1.8 | 317.4 | 35.3 | 352.7 | 16.9 |
| 38D-SP | 505.2 | 317.8 | 1.0 | 316.8 | 27.9 | 344.7 | 26.9 |
| 39D-SP | 505.4 | 328.5 | 0.5 | 328.0 | 20.1 | 348.1 | 22.0 |
| 40D-SP | 505.1 | 323.5 | 3.1 | 320.4 | 22.1 | 342.5 | 20.2 |
| 41D-SP | 505.2 | 316.9 | 1.9 | 315.0 | 15.3 | 330.3 | 34.2 |
| 42D-SP | 505.3 | 311.5 | 0.6 | 310.9 | 17.2 | 328.1 | 38.5 |
| 43D-SP | 505.5 | 330.8 | 0.5 | 330.3 | 26.2 | 356.5 | 13.6 |
| 44D-SP | 505.2 | 308.4 | 0.8 | 307.6 | 10.7 | 318.3 | 48.6 |
| 45D-SP | 505.2 | 313.0 | 1.0 | 312.0 | 14.5 | 326.5 | 14.8 |
| 46D-SP | 505.1 | 315.2 | 1.5 | 313.7 | 31.2 | 344.9 | 21.1 |
| 47D-SP | 505.2 | 313.4 | 1.1 | 312.3 | 26.5 | 338.8 | 24.3 |
| 48D-SP | 505.1 | 316.4 | 1.6 | 314.8 | 34.6 | 349.4 | 21.5 |
| 49D-SP | 505.5 | 311.6 | 1.6 | 310.0 | 16.8 | 326.8 | 24.3 |
| 50D-SP | 505.0 | 295.3 | 1.7 | 293.6 | 36.1 | 329.7 | 33.9 |
| 51D-SP | 504.9 | 328.0 | 2.0 | 326.0 | 24.2 | 350.2 | 17.1 |
| 52D-SP | 505.6 | 334.9 | 1.1 | 333.8 | 22.8 | 356.6 | 16.9 |
| 53D-SP | 505.3 | 317.8 | 0.1 | 317.7 | 25.4 | 343.1 | 25.7 |
| 54D-SP | 505.5 | 323.7 | 0.7 | 323.0 | 18.1 | 341.1 | 24.5 |
| 55D-SP | 505.0 | 321.2 | 1.0 | 320.2 | 33.4 | 353.6 | 16.0 |
| 56D-SP | 505.3 | 338.5 | 0.2 | 338.3 | 16.9 | 355.2 | 18.0 |
| 57D-SP | 505.2 | 289.2 | 1.4 | 287.8 | 37.3 | 325.1 | 36.0 |
| 58D-SP | 505.2 | 316.4 | 0.4 | 316.0 | 23.5 | 339.5 | 24.2 |
| 59D-R | 505.3 | 352.4 | 1.6 | 350.8 | 21.4 | 372.2 | 16.9 |
| 60D-R | 505.2 | 359.1 | 1.1 | 358.0 | 7.2 | 365.2 | 20.2 |
| 61D-R | 505.3 | 277.0 | 3.4 | 273.6 | 83.6 | 357.2 | 22.6 |
| 62D-R | 505.1 | 256.8 | 0.7 | 256.1 | 72.5 | 328.6 | 33.7 |
| 63D-R | 504.9 | 342.8 | 0.9 | 341.9 | 14.4 | 356.3 | 29.1 |
| 64D-R | 505.4 | 339.1 | 1.1 | 338.0 | 21.8 | 359.8 | 26.7 |
| 65D-R | 505.0 | 329.0 | 0.3 | 328.7 | 18.8 | 347.5 | 38.4 |
| 66D-R | 505.2 | 357.8 | 2.0 | 355.8 | 14.9 | 370.7 | 17.3 |
| 67D-R | 505.0 | 342.3 | 0.9 | 341.4 | 7.5 | 348.9 | 34.4 |
| 68D-R | 505.0 | 345.4 | 4.9 | 340.5 | 11.4 | 351.9 | 32.1 |
| 69D-R | 504.9 | 352.8 | 4.2 | 348.6 | 19.4 | 368.0 | 18.9 |
| 70D-R | 505.4 | 328.1 | 1.6 | 326.5 | 45.7 | 372.2 | 17.8 |

**Table A. Continued**

| Sample Code | Cleaned Sample Weight | Kernels Riding the Screen | Damaged Kernels | Sound Mature Kernels | Sound Splits | Total Sound Mature Kernels | Other Kernels |
|---|---|---|---|---|---|---|---|
| 71D-R | 505.1 | 363.9 | 1.5 | 362.4 | 10.2 | 372.6 | 14.0 |
| 72D-R | 505.1 | 284.6 | 1.6 | 283.0 | 77.5 | 360.5 | 21.4 |
| 73D-R | 505.4 | 316.1 | 3.1 | 313.0 | 20.6 | 333.6 | 40.7 |
| 74D-R | 504.9 | 300.2 | 0.6 | 299.6 | 65.6 | 365.2 | 21.5 |
| 75D-R | 504.9 | 285.6 | 1.4 | 284.2 | 82.0 | 366.2 | 19.0 |
| 76D-R | 504.9 | 300.9 | 2.3 | 298.6 | 41.3 | 339.9 | 43.0 |
| 77D-R | 505.3 | 299.1 | 0.6 | 298.5 | 75.1 | 373.6 | 17.3 |
| 78D-R | 505.0 | 359.1 | 2.9 | 356.2 | 29.0 | 385.2 | 13.0 |
| 79D-R | 505.0 | 308.4 | 1.2 | 307.2 | 34.8 | 342.0 | 45.8 |
| 80D-R | 505.8 | 323.2 | 0.8 | 322.4 | 62.6 | 385.0 | 14.2 |
| 81D-R | 505.6 | 324.3 | 1.3 | 323.0 | 40.2 | 363.2 | 25.2 |
| 82D-R | 505.3 | 309.0 | 3.1 | 305.9 | 56.3 | 362.2 | 24.9 |
| 83D-R | 505.2 | 344.9 | 1.8 | 343.1 | 32.7 | 375.8 | 23.5 |

**Table A. Extended**

| Damaged Splits | Total Damage | Total Kernels | Hulls | Total Kernels and Hulls | Weight Discrepancy | Grader Code | Sample Code |
|---|---|---|---|---|---|---|---|
| 0.0 | 2.5 | 368.5 | 130.0 | 498.5 | 1.9 | 1 | 1A-SP |
| 0.0 | 0.2 | 369.0 | 130.3 | 499.3 | 1.3 | 1 | 2A-SP |
| 0.0 | 0.3 | 367.7 | 130.3 | 498.0 | 1.9 | 1 | 3A-SP |
| 0.8 | 2.3 | 366.2 | 132.9 | 499.1 | 1.0 | 1 | 4A-SP |
| 0.0 | 0.0 | 364.8 | 134.3 | 499.1 | 1.5 | 1 | 5A-SP |
| 0.0 | 1.6 | 364.8 | 134.6 | 499.4 | 0.4 | 1 | 6A-SP |
| 0.0 | 0.0 | 364.0 | 134.3 | 498.3 | 1.8 | 1 | 7A-SP |
| 0.0 | 0.1 | 363.6 | 134.8 | 498.4 | 1.7 | 1 | 8A-SP |
| 0.3 | 1.1 | 367.4 | 130.6 | 498.0 | 2.1 | 1 | 9A-SP |
| 0.0 | 0.5 | 367.0 | 131.2 | 498.2 | 1.9 | 1 | 10A-SP |
| 0.0 | 0.4 | 369.9 | 130.4 | 500.3 | 0.0 | 1 | 11A-SP |
| 1.4 | 4.4 | 366.4 | 132.5 | 498.9 | 1.4 | 2 | 12A-SP |
| 0.8 | 1.8 | 363.5 | 105.5 | 469.0 | 31.6 | 2 | 13A-SP |
| 0.4 | 0.8 | 366.5 | 131.3 | 497.8 | 1.7 | 2 | 14A-SP |
| 0.4 | 0.7 | 365.6 | 131.8 | 497.4 | 2.0 | 2 | 15A-SP |
| 0.0 | 0.4 | 359.8 | 130.9 | 490.7 | 9.2 | 2 | 16A-SP |
| 2.1 | 3.5 | 365.0 | 132.7 | 497.7 | 2.0 | 2 | 17A-SP |
| 1.3 | 1.8 | 363.2 | 131.4 | 494.6 | 5.8 | 3 | 18A-SP |
| 0.1 | 1.5 | 364.7 | 133.0 | 497.7 | 2.4 | 3 | 19A-SP |
| 0.0 | 0.9 | 367.7 | 130.2 | 497.9 | 2.2 | 3 | 20A-SP |
| 0.0 | 0.4 | 368.6 | 128.7 | 497.3 | 2.5 | 3 | 21A-SP |
| 0.3 | 1.2 | 366.4 | 131.3 | 497.7 | 2.3 | 3 | 22A-SP |
| 0.7 | 2.5 | 367.2 | 129.2 | 496.4 | 3.3 | 2 | 23A-SP |
| 1.0 | 4.1 | 367.1 | 131.3 | 498.4 | 1.9 | 2 | 24A-SP |
| 0.0 | 1.3 | 365.5 | 132.3 | 497.8 | 2.7 | 2 | 25A-SP |
| 0.5 | 0.5 | 367.9 | 130.5 | 498.4 | 2.0 | 3 | 26A-SP |
| 1.1 | 1.6 | 361.7 | 135.3 | 497.0 | 2.6 | 3 | 27A-SP |
| 0.8 | 1.1 | 368.1 | 129.8 | 497.9 | 1.9 | 3 | 28A-SP |
| 0.2 | 1.3 | 365.3 | 133.4 | 498.7 | 1.5 | 1 | 29A-SP |
| 0.7 | 0.9 | 367.7 | 130.1 | 497.8 | 2.2 | 3 | 30A-SP |
| 0.9 | 1.2 | 366.2 | 131.2 | 497.4 | 2.1 | 1 | 31A-SP |
| 0.0 | 1.4 | 371.8 | 127.7 | 499.5 | 0.2 | 1 | 32A-SP |
| 0.0 | 0.4 | 365.4 | 132.0 | 497.4 | 2.6 | 1 | 33A-SP |
| 0.7 | 1.0 | 367.6 | 130.3 | 497.9 | 2.1 | 1 | 34A-SP |
| 0.7 | 1.4 | 369.0 | 130.5 | 499.5 | 0.4 | 1 | 35A-SP |
| 0.3 | 0.3 | 366.1 | 131.7 | 497.8 | 2.1 | 1 | 36A-SP |
| 0.6 | 1.5 | 370.9 | 125.7 | 496.6 | 3.1 | 1 | 37A-SP |
| 0.1 | 0.9 | 366.1 | 131.8 | 497.9 | 2.1 | 1 | 38A-SP |
| 0.4 | 1.3 | 363.7 | 133.8 | 497.5 | 2.9 | 2 | 39A-SP |

**Table A. Extended**

| Damaged Splits | Total Damage | Total Kernels | Hulls | Total Kernels and Hulls | Weight Discrepancy | Grader Code | Sample Code |
|---|---|---|---|---|---|---|---|
| 1.6 | 5.7 | 366.9 | 132.4 | 499.3 | 0.6 | 2 | 40A-SP |
| 0.6 | 2.9 | 365.9 | 131.2 | 497.1 | 3.1 | 2 | 41A-SP |
| 0.0 | 2.4 | 367.4 | 130.4 | 497.8 | 2.3 | 2 | 42A-SP |
| 1.3 | 3.3 | 364.0 | 131.9 | 495.9 | 4.1 | 2 | 43A-SP |
| 0.9 | 2.3 | 368.3 | 129.2 | 497.5 | 2.6 | 2 | 44A-SP |
| 0.2 | 1.4 | 339.1 | 141.2 | 480.3 | 19.9 | 1 | 45A-SP |
| 1.2 | 7.1 | 368.5 | 129.0 | 497.5 | 2.9 | 2 | 46A-SP |
| 1.1 | 3.2 | 362.0 | 134.2 | 496.2 | 3.9 | 2 | 47A-SP |
| 1.2 | 2.7 | 371.3 | 126.5 | 497.8 | 2.4 | 2 | 48A-SP |
| 0.5 | 1.4 | 355.8 | 139.3 | 495.1 | 5.1 | 2 | 49A-SP |
| 1.8 | 2.8 | 362.1 | 134.2 | 496.3 | 3.7 | 2 | 50A-SP |
| 0.8 | 2.0 | 367.4 | 131.2 | 498.6 | 1.4 | 3 | 51A-SP |
| 0.9 | 3.2 | 369.9 | 129.1 | 499.0 | 0.7 | 3 | 52A-SP |
| 0.9 | 1.7 | 363.2 | 134.8 | 498.0 | 1.4 | 3 | 53A-SP |
| 1.2 | 1.2 | 363.2 | 134.3 | 497.5 | 2.9 | 3 | 54A-SP |
| 0.8 | 0.8 | 368.3 | 130.1 | 498.4 | 1.7 | 3 | 55A-SP |
| 0.0 | 2.7 | 371.4 | 127.7 | 499.1 | 1.4 | 3 | 56A-SP |
| 0.9 | 1.5 | 361.8 | 135.6 | 497.4 | 2.5 | 3 | 57A-SP |
| 0.2 | 0.2 | 363.8 | 134.2 | 498.0 | 2.2 | 3 | 58A-SP |
| 0.4 | 2.1 | 389.8 | 109.8 | 499.6 | 0.4 | 3 | 59A-R |
| 0.0 | 0.6 | 385.1 | 112.2 | 497.3 | 2.4 | 1 | 60A-R |
| 2.4 | 6.0 | 383.5 | 114.7 | 498.2 | 2.3 | 3 | 61A-R |
| 2.9 | 7.1 | 362.3 | 135.4 | 497.7 | 2.7 | 3 | 62A-R |
| 0.4 | 0.4 | 381.3 | 116.0 | 497.3 | 3.2 | 1 | 63A-R |
| 0.7 | 4.3 | 391.4 | 110.6 | 502.0 | -1.6 | 3 | 64A-R |
| 0.2 | 3.6 | 383.9 | 113.6 | 497.5 | 2.8 | 3 | 65A-R |
| 0.0 | 2.5 | 389.6 | 106.9 | 496.5 | 3.3 | 3 | 66A-R |
| 0.0 | 1.5 | 383.4 | 113.9 | 497.3 | 2.9 | 3 | 67A-R |
| 0.0 | 3.7 | 388.6 | 108.4 | 497.0 | 2.8 | 3 | 68A-R |
| 0.2 | 2.6 | 385.5 | 110.6 | 496.1 | 3.5 | 3 | 69A-R |
| 2.3 | 4.1 | 390.6 | 106.1 | 496.7 | 3.5 | 2 | 70A-R |
| 0.0 | 0.6 | 387.0 | 110.4 | 497.4 | 2.0 | 2 | 71A-R |
| 4.5 | 5.6 | 379.2 | 116.9 | 496.1 | 4.1 | 2 | 72A-R |
| 0.4 | 1.8 | 371.2 | 125.1 | 496.3 | 3.6 | 2 | 73A-R |
| 1.1 | 2.3 | 387.1 | 110.3 | 497.4 | 2.5 | 2 | 74A-R |
| 1.9 | 5.1 | 388.2 | 109.6 | 497.8 | 2.3 | 2 | 75A-R |
| 0.8 | 2.0 | 379.7 | 119.1 | 498.8 | 1.6 | 2 | 76A-R |
| 0.8 | 1.8 | 388.3 | 110.5 | 498.8 | 1.3 | 2 | 77A-R |
| 1.0 | 1.4 | 396.8 | 102.8 | 499.6 | 0.7 | 2 | 78A-R |
| 0.0 | 1.5 | 379.6 | 118.8 | 498.4 | 1.5 | 2 | 79A-R |

**Table A. Extended**

| Damaged Splits | Total Damage | Total Kernels | Hulls | Total Kernels and Hulls | Weight Discrepancy | Grader Code | Sample Code |
|---|---|---|---|---|---|---|---|
| 1.1 | 2.3 | 393.8 | 104.3 | 498.1 | 1.7 | 2 | 80A-R |
| 0.4 | 3.6 | 381.4 | 117.4 | 498.8 | 1.5 | 2 | 81A-R |
| 1.2 | 5.0 | 384.2 | 113.9 | 498.1 | 1.3 | 2 | 82A-R |
| 1.2 | 3.4 | 396.4 | 102.7 | 499.1 | 0.7 | 2 | 83A-R |
| 1.0 | 1.4 | 368.0 | 130.0 | 498.0 | 3.8 | 1 | 1B-SP |
| 0.1 | 0.1 | 366.1 | 133.6 | 499.7 | 2.2 | 1 | 2B-SP |
| 0.5 | 0.7 | 368.0 | 132.7 | 500.7 | 1.1 | 1 | 3B-SP |
| 0.5 | 2.0 | 363.4 | 137.5 | 500.9 | 1.0 | 1 | 4B-SP |
| 0.6 | 1.9 | 366.0 | 134.3 | 500.3 | 1.3 | 1 | 5B-SP |
| 0.4 | 0.9 | 365.3 | 134.8 | 500.1 | 1.6 | 1 | 6B-SP |
| 0.0 | 1.0 | 365.6 | 133.3 | 498.9 | 2.7 | 1 | 7B-SP |
| 0.7 | 0.7 | 366.5 | 134.1 | 500.6 | 0.7 | 1 | 8B-SP |
| 0.6 | 0.6 | 363.5 | 136.8 | 500.3 | 1.5 | 1 | 9B-SP |
| 0.3 | 0.7 | 367.4 | 132.5 | 499.9 | 1.7 | 1 | 10B-SP |
| 0.2 | 1.8 | 368.8 | 131.8 | 500.6 | 1.2 | 2 | 11B-SP |
| 0.0 | 0.6 | 366.7 | 133.0 | 499.7 | 1.8 | 2 | 12B-SP |
| 1.1 | 3.0 | 365.0 | 135.0 | 500.0 | 1.7 | 2 | 13B-SP |
| 0.3 | 2.2 | 365.3 | 133.7 | 499.0 | 2.8 | 2 | 14B-SP |
| 0.1 | 0.3 | 365.6 | 133.7 | 499.3 | 2.6 | 3 | 15B-SP |
| 0.0 | 0.0 | 368.1 | 130.8 | 498.9 | 2.9 | 3 | 16B-SP |
| 2.5 | 3.7 | 368.0 | 132.1 | 500.1 | 1.6 | 2 | 17B-SP |
| 0.0 | 0.0 | 366.1 | 133.1 | 499.2 | 2.4 | 2 | 18B-SP |
| 0.1 | 0.3 | 365.7 | 134.0 | 499.7 | 2.2 | 3 | 19B-SP |
| 0.0 | 1.1 | 367.5 | 132.1 | 499.6 | 1.9 | 3 | 20B-SP |
| 1.2 | 2.6 | 362.8 | 135.9 | 498.7 | 2.9 | 3 | 21B-SP |
| 0.0 | 0.5 | 370.4 | 128.8 | 499.2 | 2.3 | 3 | 22B-SP |
| 0.0 | 0.7 | 369.7 | 129.0 | 498.7 | 3.2 | 2 | 23B-SP |
| 1.0 | 2.7 | 368.8 | 131.0 | 499.8 | 1.8 | 2 | 24B-SP |
| 0.0 | 0.5 | 367.3 | 131.9 | 499.2 | 2.3 | 2 | 25B-SP |
| 0.0 | 0.6 | 367.6 | 133.6 | 501.2 | 0.4 | 3 | 26B-SP |
| 0.0 | 0.0 | 366.7 | 131.8 | 498.5 | 2.7 | 1 | 27B-SP |
| 0.0 | 1.9 | 365.7 | 132.9 | 498.6 | 2.9 | 1 | 28B-SP |
| 0.4 | 1.3 | 367.2 | 131.4 | 498.6 | 3.4 | 1 | 29B-SP |
| 0.5 | 1.3 | 365.1 | 133.8 | 498.9 | 2.6 | 1 | 30B-SP |
| 0.6 | 0.6 | 368.7 | 130.8 | 499.5 | 2.2 | 1 | 31B-SP |
| 0.7 | 1.0 | 366.1 | 133.0 | 499.1 | 2.4 | 1 | 32B-SP |
| 0.5 | 0.5 | 365.8 | 133.4 | 499.2 | 2.5 | 1 | 33B-SP |
| 0.9 | 2.0 | 368.3 | 131.5 | 499.8 | 2.1 | 1 | 34B-SP |
| 0.6 | 1.8 | 367.0 | 130.1 | 497.1 | 4.8 | 2 | 35B-SP |
| 0.8 | 0.8 | 366.2 | 131.9 | 498.1 | 3.4 | 1 | 36B-SP |

**Table A. Extended**

| Damaged Splits | Total Damage | Total Kernels | Hulls | Total Kernels and Hulls | Weight Discrepancy | Grader Code | Sample Code |
|---|---|---|---|---|---|---|---|
| 1.3 | 3.5 | 370.0 | 129.3 | 499.3 | 2.7 | 1 | 37B-SP |
| 0.1 | 0.7 | 367.8 | 129.0 | 496.8 | 4.7 | 1 | 38B-SP |
| 0.6 | 1.6 | 365.3 | 133.4 | 498.7 | 3.0 | 2 | 39B-SP |
| 0.7 | 3.0 | 364.7 | 133.5 | 498.2 | 3.2 | 2 | 40B-SP |
| 0.7 | 3.6 | 367.1 | 131.7 | 498.8 | 3.0 | 2 | 41B-SP |
| 0.3 | 2.7 | 366.0 | 133.0 | 499.0 | 2.4 | 2 | 42B-SP |
| 0.4 | 0.9 | 363.5 | 134.1 | 497.6 | 4.0 | 2 | 43B-SP |
| 0.4 | 0.7 | 368.6 | 131.5 | 500.1 | 1.8 | 1 | 44B-SP |
| 0.3 | 1.3 | 333.7 | 155.7 | 489.4 | 12.2 | 2 | 45B-SP |
| 1.1 | 2.7 | 368.4 | 131.0 | 499.4 | 2.5 | 2 | 46B-SP |
| 1.5 | 2.8 | 365.4 | 133.1 | 498.5 | 3.2 | 2 | 47B-SP |
| 0.9 | 1.5 | 372.1 | 127.1 | 499.2 | 2.8 | 2 | 48B-SP |
| 1.0 | 3.1 | 352.3 | 144.1 | 496.4 | 5.4 | 2 | 49B-SP |
| 1.2 | 1.9 | 359.6 | 139.0 | 498.6 | 3.2 | 2 | 50B-SP |
| 0.9 | 2.1 | 363.2 | 136.0 | 499.2 | 2.4 | 3 | 51B-SP |
| 0.7 | 2.3 | 372.5 | 128.5 | 501.0 | 1.1 | 3 | 52B-SP |
| 0.8 | 1.9 | 364.0 | 134.7 | 498.7 | 2.9 | 3 | 53B-SP |
| 0.7 | 2.5 | 368.8 | 131.4 | 500.2 | 1.6 | 3 | 54B-SP |
| 0.0 | 0.8 | 365.5 | 134.4 | 499.9 | 1.9 | 3 | 55B-SP |
| 0.6 | 3.1 | 373.6 | 126.4 | 500.0 | 1.8 | 3 | 56B-SP |
| 1.7 | 4.3 | 362.3 | 136.9 | 499.2 | 2.3 | 3 | 57B-SP |
| 0.6 | 0.7 | 365.3 | 134.5 | 499.8 | 1.8 | 3 | 58B-SP |
| 0.0 | 2.6 | 389.7 | 109.5 | 499.2 | 2.8 | 3 | 59B-R |
| 0.8 | 2.3 | 387.9 | 113.0 | 500.9 | 1.2 | 1 | 60B-R |
| 1.3 | 2.5 | 387.6 | 112.0 | 499.6 | 1.9 | 1 | 61B-R |
| 3.3 | 5.8 | 363.5 | 134.1 | 497.6 | 4.1 | 3 | 62B-R |
| 0.5 | 1.5 | 385.0 | 113.6 | 498.6 | 3.3 | 3 | 63B-R |
| 0.6 | 2.7 | 387.6 | 111.5 | 499.1 | 2.8 | 3 | 64B-R |
| 0.2 | 2.5 | 385.2 | 114.3 | 499.5 | 2.2 | 3 | 65B-R |
| 0.7 | 2.8 | 387.3 | 112.0 | 499.3 | 2.4 | 3 | 66B-R |
| 0.1 | 2.1 | 381.7 | 117.6 | 499.3 | 2.4 | 3 | 67B-R |
| 0.0 | 2.7 | 386.6 | 112.9 | 499.5 | 2.5 | 3 | 68B-R |
| 0.6 | 3.3 | 385.5 | 113.8 | 499.3 | 2.4 | 3 | 69B-R |
| 2.9 | 6.3 | 389.5 | 109.0 | 498.5 | 3.3 | 3 | 70B-R |
| 0.0 | 1.6 | 392.8 | 109.1 | 501.9 | -0.2 | 2 | 71B-R |
| 2.3 | 3.4 | 384.3 | 114.8 | 499.1 | 2.3 | 2 | 72B-R |
| 0.3 | 1.6 | 371.3 | 127.4 | 498.7 | 2.9 | 2 | 73B-R |
| 1.2 | 3.2 | 390.5 | 109.3 | 499.8 | 2.2 | 2 | 74B-R |
| 1.1 | 3.4 | 386.0 | 112.7 | 498.7 | 2.8 | 2 | 75B-R |
| 1.6 | 4.6 | 380.9 | 119.6 | 500.5 | 1.1 | 2 | 76B-R |

**Table A. Extended**

| Damaged Splits | Total Damage | Total Kernels | Hulls | Total Kernels and Hulls | Weight Discrepancy | Grader Code | Sample Code |
|---|---|---|---|---|---|---|---|
| 3.0 | 4.6 | 387.4 | 113.0 | 500.4 | 1.4 | 2 | 77B-R |
| 0.3 | 1.0 | 396.7 | 103.7 | 500.4 | 1.2 | 2 | 78B-R |
| 1.6 | 4.1 | 383.4 | 118.3 | 501.7 | 0.3 | 2 | 79B-R |
| 2.0 | 2.4 | 397.9 | 102.7 | 500.6 | 1.2 | 2 | 80B-R |
| 1.0 | 4.8 | 384.2 | 116.0 | 500.2 | 1.5 | 2 | 81B-R |
| 3.0 | 6.3 | 387.4 | 114.4 | 501.8 | 0.1 | 2 | 82B-R |
| 0.0 | 3.8 | 390.7 | 110.6 | 501.3 | 0.5 | 2 | 83B-R |
| 0.0 | 1.1 | 371.2 | 130.6 | 501.8 | 1.8 | 1 | 1C-SP |
| 0.2 | 0.8 | 368.5 | 134.2 | 502.7 | 1.1 | 1 | 2C-SP |
| 0.2 | 1.3 | 363.9 | 138.1 | 502.0 | 1.4 | 1 | 3C-SP |
| 0.6 | 2.5 | 365.9 | 135.8 | 501.7 | 2.0 | 1 | 4C-SP |
| 0.0 | 0.0 | 365.5 | 135.7 | 501.2 | 2.1 | 1 | 5C-SP |
| 0.1 | 0.1 | 367.9 | 134.3 | 502.2 | 1.5 | 1 | 6C-SP |
| 0.6 | 1.1 | 365.4 | 136.1 | 501.5 | 1.6 | 1 | 7C-SP |
| 0.1 | 0.1 | 366.6 | 134.4 | 501.0 | 2.5 | 1 | 8C-SP |
| 0.0 | 0.0 | 371.9 | 129.6 | 501.5 | 1.8 | 1 | 9C-SP |
| 0.4 | 0.9 | 366.7 | 135.4 | 502.1 | 1.6 | 1 | 10C-SP |
| 0.0 | 1.0 | 369.1 | 132.4 | 501.5 | 2.1 | 2 | 11C-SP |
| 0.2 | 0.7 | 368.3 | 131.9 | 500.2 | 3.1 | 1 | 12C-SP |
| 0.0 | 2.9 | 366.1 | 134.6 | 500.7 | 3.0 | 2 | 13C-SP |
| 0.2 | 1.9 | 368.9 | 132.2 | 501.1 | 2.1 | 2 | 14C-SP |
| 0.0 | 1.3 | 369.4 | 132.2 | 501.6 | 1.7 | 2 | 15C-SP |
| 0.3 | 0.6 | 373.9 | 128.1 | 502.0 | 1.8 | 2 | 16C-SP |
| 0.3 | 1.6 | 366.7 | 132.0 | 498.7 | 5.1 | 3 | 17C-SP |
| 0.5 | 1.4 | 368.3 | 134.1 | 502.4 | 1.3 | 3 | 18C-SP |
| 0.0 | 0.2 | 365.3 | 134.8 | 500.1 | 3.5 | 3 | 19C-SP |
| 0.0 | 0.0 | 368.4 | 132.2 | 500.6 | 2.7 | 3 | 20C-SP |
| 0.6 | 1.9 | 368.0 | 133.1 | 501.1 | 2.4 | 3 | 21C-SP |
| 0.2 | 1.3 | 370.6 | 131.0 | 501.6 | 1.8 | 3 | 22C-SP |
| 0.3 | 1.3 | 369.8 | 130.6 | 500.4 | 3.4 | 3 | 23C-SP |
| 2.5 | 5.4 | 366.7 | 135.4 | 502.1 | 1.6 | 2 | 24C-SP |
| 0.6 | 0.6 | 369.5 | 131.7 | 501.2 | 2.6 | 2 | 25C-SP |
| 0.3 | 2.0 | 363.3 | 137.0 | 500.3 | 2.9 | 3 | 26C-SP |
| 1.0 | 1.7 | 367.9 | 133.8 | 501.7 | 1.8 | 3 | 27C-SP |
| 0.5 | 1.5 | 365.9 | 135.0 | 500.9 | 2.2 | 3 | 28C-SP |
| 1.0 | 1.7 | 367.0 | 133.8 | 500.8 | 2.3 | 3 | 29C-SP |
| 0.4 | 1.3 | 368.1 | 132.6 | 500.7 | 3.0 | 1 | 30C-SP |
| 0.0 | 0.4 | 368.2 | 131.9 | 500.1 | 3.7 | 1 | 31C-SP |
| 0.0 | 0.8 | 367.9 | 133.0 | 500.9 | 2.5 | 1 | 32C-SP |
| 0.0 | 0.5 | 367.3 | 133.7 | 501.0 | 2.3 | 1 | 33C-SP |

**Table A. Extended**

| Damaged Splits | Total Damage | Total Kernels | Hulls | Total Kernels and Hulls | Weight Discrepancy | Grader Code | Sample Code |
|---|---|---|---|---|---|---|---|
| 0.0 | 0.0 | 371.2 | 129.8 | 501.0 | 2.2 | 1 | 34C-SP |
| 0.5 | 1.0 | 369.3 | 131.1 | 500.4 | 2.8 | 1 | 35C-SP |
| 0.2 | 0.6 | 365.9 | 134.3 | 500.2 | 3.3 | 1 | 36C-SP |
| 0.7 | 2.0 | 373.6 | 128.3 | 501.9 | 1.8 | 1 | 37C-SP |
| 0.0 | 1.9 | 346.3 | 109.4 | 455.7 | 47.7 | 1 | 38C-SP |
| 0.0 | 0.0 | 366.1 | 134.6 | 500.7 | 2.6 | 1 | 39C-SP |
| 0.4 | 1.2 | 367.6 | 133.7 | 501.3 | 2.0 | 2 | 40C-SP |
| 0.6 | 3.1 | 367.1 | 133.7 | 500.8 | 2.6 | 2 | 41C-SP |
| 0.8 | 2.4 | 366.0 | 132.4 | 498.4 | 4.8 | 2 | 42C-SP |
| 1.2 | 1.9 | 366.8 | 133.2 | 500.0 | 3.2 | 2 | 43C-SP |
| 0.2 | 2.3 | 368.3 | 132.7 | 501.0 | 2.8 | 2 | 44C-SP |
| 0.0 | 0.7 | 339.2 | 153.3 | 492.5 | 11.1 | 2 | 45C-SP |
| 1.9 | 3.8 | 371.7 | 129.0 | 500.7 | 2.6 | 2 | 46C-SP |
| 2.2 | 6.3 | 364.0 | 135.5 | 499.5 | 3.7 | 2 | 47C-SP |
| 0.7 | 3.1 | 371.6 | 128.4 | 500.0 | 3.3 | 2 | 48C-SP |
| 0.5 | 1.7 | 355.1 | 144.2 | 499.3 | 4.3 | 2 | 49C-SP |
| 0.4 | 1.2 | 362.4 | 137.1 | 499.5 | 4.1 | 2 | 50C-SP |
| 0.9 | 1.7 | 367.6 | 134.8 | 502.4 | 1.0 | 3 | 51C-SP |
| 1.0 | 2.1 | 371.9 | 129.8 | 501.7 | 2.4 | 3 | 52C-SP |
| 1.6 | 2.2 | 367.3 | 134.1 | 501.4 | 2.2 | 3 | 53C-SP |
| 0.0 | 1.3 | 371.5 | 129.9 | 501.4 | 2.2 | 3 | 54C-SP |
| 0.6 | 1.9 | 371.9 | 129.8 | 501.7 | 1.8 | 3 | 55C-SP |
| 0.5 | 2.1 | 374.0 | 128.5 | 502.5 | 1.3 | 3 | 56C-SP |
| 1.6 | 3.1 | 365.2 | 136.3 | 501.5 | 1.9 | 3 | 57C-SP |
| 0.0 | 0.0 | 366.5 | 135.8 | 502.3 | 1.0 | 3 | 58C-SP |
| 0.3 | 1.9 | 392.7 | 112.1 | 504.8 | -1.7 | 3 | 59C-R |
| 0.1 | 0.1 | 388.6 | 113.0 | 501.6 | 2.1 | 3 | 60C-R |
| 1.6 | 5.5 | 383.1 | 116.3 | 499.4 | 3.9 | 3 | 61C-R |
| 3.2 | 5.0 | 372.3 | 128.2 | 500.5 | 3.1 | 3 | 62C-R |
| 0.0 | 0.6 | 386.9 | 114.3 | 501.2 | 2.3 | 1 | 63C-R |
| 0.7 | 1.4 | 386.9 | 114.5 | 501.4 | 1.8 | 1 | 64C-R |
| 1.7 | 4.0 | 386.1 | 115.2 | 501.3 | 2.0 | 1 | 65C-R |
| 0.0 | 0.0 | 389.6 | 109.6 | 499.2 | 4.4 | 3 | 66C-R |
| 0.3 | 2.3 | 390.3 | 114.1 | 504.4 | -1.2 | 3 | 67C-R |
| 0.7 | 4.5 | 387.7 | 113.3 | 501.0 | 2.6 | 3 | 68C-R |
| 0.0 | 1.3 | 389.6 | 110.8 | 500.4 | 3.1 | 3 | 69C-R |
| 2.3 | 5.7 | 393.7 | 108.0 | 501.7 | 2.1 | 3 | 70C-R |
| 0.0 | 1.8 | 386.3 | 114.3 | 500.6 | 2.8 | 2 | 71C-R |
| 1.9 | 5.9 | 376.3 | 114.8 | 491.1 | 12.8 | 2 | 72C-R |
| 0.8 | 3.7 | 374.4 | 125.8 | 500.2 | 3.1 | 2 | 73C-R |

**Table A. Extended**

| Damaged Splits | Total Damage | Total Kernels | Hulls | Total Kernels and Hulls | Weight Discrepancy | Grader Code | Sample Code |
|---|---|---|---|---|---|---|---|
| 1.1 | 3.4 | 391.8 | 109.2 | 501.0 | 2.6 | 2 | 74C-R |
| 3.4 | 6.2 | 385.4 | 115.8 | 501.2 | 2.2 | 2 | 75C-R |
| 1.1 | 4.7 | 382.0 | 115.4 | 497.4 | 6.1 | 2 | 76C-R |
| 4.4 | 6.3 | 392.3 | 109.9 | 502.2 | 1.4 | 2 | 77C-R |
| 0.4 | 2.2 | 401.8 | 100.4 | 502.2 | 1.5 | 2 | 78C-R |
| 0.5 | 2.4 | 383.9 | 117.4 | 501.3 | 2.0 | 2 | 79C-R |
| 1.5 | 3.1 | 396.2 | 106.6 | 502.8 | 0.8 | 2 | 80C-R |
| 1.3 | 4.6 | 385.8 | 116.8 | 502.6 | 1.7 | 2 | 81C-R |
| 2.1 | 4.6 | 388.4 | 114.7 | 503.1 | 1.0 | 2 | 82C-R |
| 0.0 | 1.6 | 397.4 | 104.7 | 502.1 | 1.5 | 2 | 83C-R |
| 0.5 | 1.3 | 371.8 | 130.5 | 502.3 | 2.8 | 1 | 1D-SP |
| 0.0 | 0.4 | 366.9 | 136.6 | 503.5 | 1.7 | 1 | 2D-SP |
| 0.2 | 0.6 | 370.8 | 133.1 | 503.9 | 0.9 | 1 | 3D-SP |
| 0.5 | 1.1 | 369.2 | 135.4 | 504.6 | 0.6 | 1 | 4D-SP |
| 0.1 | 0.6 | 371.6 | 131.7 | 503.3 | 1.7 | 1 | 5D-SP |
| 0.3 | 1.3 | 370.7 | 133.7 | 504.4 | 1.2 | 1 | 6D-SP |
| 0.0 | 0.5 | 369.5 | 133.1 | 502.6 | 2.3 | 1 | 7D-SP |
| 0.0 | 1.5 | 369.5 | 134.0 | 503.5 | 1.5 | 1 | 8D-SP |
| 0.0 | 0.7 | 369.0 | 134.7 | 503.7 | 1.3 | 1 | 9D-SP |
| 0.9 | 0.9 | 367.1 | 136.6 | 503.7 | 1.5 | 1 | 10D-SP |
| 0.0 | 1.0 | 368.3 | 134.4 | 502.7 | 2.5 | 2 | 11D-SP |
| 1.2 | 3.0 | 371.8 | 131.8 | 503.6 | 1.3 | 1 | 12D-SP |
| 1.2 | 3.1 | 369.5 | 134.5 | 504.0 | 1.4 | 2 | 13D-SP |
| 0.6 | 0.8 | 368.8 | 133.6 | 502.4 | 2.7 | 2 | 14D-SP |
| 0.2 | 1.2 | 368.5 | 134.4 | 502.9 | 2.1 | 2 | 15D-SP |
| 0.0 | 1.4 | 367.4 | 132.6 | 500.0 | 4.6 | 3 | 16D-SP |
| 0.9 | 2.5 | 367.1 | 134.7 | 501.8 | 3.3 | 3 | 17D-SP |
| 0.6 | 2.1 | 393.8 | 135.1 | 528.9 | -24.2 | 3 | 18D-SP |
| 0.0 | 0.8 | 368.5 | 133.3 | 501.8 | 3.2 | 3 | 19D-SP |
| 0.0 | 1.6 | 366.2 | 136.6 | 502.8 | 2.7 | 3 | 20D-SP |
| 0.4 | 0.7 | 372.3 | 130.1 | 502.4 | 2.5 | 3 | 21D-SP |
| 0.0 | 0.0 | 366.8 | 136.0 | 502.8 | 2.2 | 3 | 22D-SP |
| 0.9 | 0.9 | 373.1 | 128.8 | 501.9 | 3.3 | 3 | 23D-SP |
| 1.0 | 3.5 | 369.8 | 133.0 | 502.8 | 2.2 | 2 | 24D-SP |
| 0.0 | 0.8 | 370.0 | 133.0 | 503.0 | 2.1 | 2 | 25D-SP |
| 0.2 | 1.1 | 367.1 | 135.9 | 503.0 | 2.1 | 3 | 26D-SP |
| 0.8 | 1.2 | 369.4 | 136.0 | 505.4 | -0.5 | 3 | 27D-SP |
| 0.0 | 0.2 | 370.0 | 132.6 | 502.6 | 2.5 | 3 | 28D-SP |
| 0.7 | 1.4 | 368.5 | 134.5 | 503.0 | 2.1 | 3 | 29D-SP |
| 0.3 | 1.8 | 371.6 | 131.4 | 503.0 | 2.3 | 3 | 30D-SP |

**Table A. Extended**

| Damaged Splits | Total Damage | Total Kernels | Hulls | Total Kernels and Hulls | Weight Discrepancy | Grader Code | Sample Code |
|---|---|---|---|---|---|---|---|
| 1.3 | 1.7 | 371.3 | 130.9 | 502.2 | 2.8 | 1 | 31D-SP |
| 0.4 | 2.2 | 371.6 | 131.5 | 503.1 | 2.1 | 1 | 32D-SP |
| 0.0 | 0.0 | 364.2 | 132.5 | 496.7 | 8.6 | 1 | 33D-SP |
| 1.0 | 1.5 | 370.2 | 132.5 | 502.7 | 2.4 | 1 | 34D-SP |
| 0.3 | 1.0 | 370.3 | 129.8 | 500.1 | 4.8 | 1 | 35D-SP |
| 0.5 | 0.5 | 368.3 | 134.6 | 502.9 | 2.3 | 1 | 36D-SP |
| 0.7 | 2.5 | 372.1 | 128.3 | 500.4 | 4.8 | 1 | 37D-SP |
| 0.0 | 1.0 | 372.6 | 129.2 | 501.8 | 3.4 | 2 | 38D-SP |
| 0.0 | 0.5 | 370.6 | 133.3 | 503.9 | 1.5 | 1 | 39D-SP |
| 1.7 | 4.8 | 367.5 | 135.7 | 503.2 | 1.9 | 2 | 40D-SP |
| 2.4 | 4.3 | 368.8 | 133.7 | 502.5 | 2.7 | 2 | 41D-SP |
| 0.5 | 1.1 | 367.7 | 135.0 | 502.7 | 2.6 | 2 | 42D-SP |
| 0.9 | 1.4 | 371.5 | 130.9 | 502.4 | 3.1 | 1 | 43D-SP |
| 0.7 | 1.5 | 368.4 | 133.3 | 501.7 | 3.5 | 2 | 44D-SP |
| 0.0 | 1.0 | 342.3 | 150.0 | 492.3 | 12.9 | 1 | 45D-SP |
| 1.7 | 3.2 | 369.2 | 133.2 | 502.4 | 2.7 | 2 | 46D-SP |
| 1.4 | 2.5 | 365.6 | 135.9 | 501.5 | 3.7 | 2 | 47D-SP |
| 1.2 | 2.8 | 373.7 | 127.8 | 501.5 | 3.6 | 2 | 48D-SP |
| 0.2 | 1.8 | 352.9 | 143.7 | 496.6 | 8.9 | 2 | 49D-SP |
| 1.4 | 3.1 | 366.7 | 135.1 | 501.8 | 3.2 | 2 | 50D-SP |
| 0.9 | 2.9 | 370.2 | 134.6 | 504.8 | 0.1 | 3 | 51D-SP |
| 0.6 | 1.7 | 375.2 | 129.0 | 504.2 | 1.4 | 3 | 52D-SP |
| 0.5 | 0.6 | 369.4 | 133.5 | 502.9 | 2.4 | 3 | 53D-SP |
| 1.3 | 2.0 | 367.6 | 136.0 | 503.6 | 1.9 | 3 | 54D-SP |
| 0.5 | 1.5 | 371.1 | 132.0 | 503.1 | 1.9 | 3 | 55D-SP |
| 0.9 | 1.1 | 374.3 | 129.5 | 503.8 | 1.5 | 3 | 56D-SP |
| 1.2 | 2.6 | 363.7 | 138.3 | 502.0 | 3.2 | 3 | 57D-SP |
| 0.3 | 0.7 | 364.4 | 133.2 | 497.6 | 7.6 | 3 | 58D-SP |
| 0.0 | 1.6 | 390.7 | 112.6 | 503.3 | 2.0 | 3 | 59D-R |
| 0.2 | 1.3 | 386.7 | 115.6 | 502.3 | 2.9 | 1 | 60D-R |
| 3.8 | 7.2 | 387.0 | 114.5 | 501.5 | 3.8 | 3 | 61D-R |
| 0.8 | 1.5 | 363.8 | 137.5 | 501.3 | 3.8 | 3 | 62D-R |
| 0.4 | 1.3 | 386.7 | 115.0 | 501.7 | 3.2 | 1 | 63D-R |
| 0.2 | 1.3 | 387.8 | 115.6 | 503.4 | 2.0 | 1 | 64D-R |
| 0.5 | 0.8 | 386.7 | 116.4 | 503.1 | 1.9 | 1 | 65D-R |
| 0.2 | 2.2 | 390.2 | 111.7 | 501.9 | 3.3 | 3 | 66D-R |
| 0.4 | 1.3 | 384.6 | 116.2 | 500.8 | 4.2 | 3 | 67D-R |
| 0.8 | 5.7 | 389.7 | 113.2 | 502.9 | 2.1 | 3 | 68D-R |
| 1.0 | 5.2 | 392.1 | 110.8 | 502.9 | 2.0 | 3 | 69D-R |
| 0.0 | 1.6 | 391.6 | 111.5 | 503.1 | 2.3 | 3 | 70D-R |

**Table A. Extended**

| Damaged Splits | Total Damage | Total Kernels | Hulls | Total Kernels and Hulls | Weight Discrepancy | Grader Code | Sample Code |
|---|---|---|---|---|---|---|---|
| 0.4 | 1.9 | 388.5 | 108.2 | 496.7 | 8.4 | 2 | 71D-R |
| 3.8 | 5.4 | 387.3 | 115.4 | 502.7 | 2.4 | 2 | 72D-R |
| 0.0 | 3.1 | 377.4 | 124.7 | 502.1 | 3.3 | 2 | 73D-R |
| 1.6 | 2.2 | 388.9 | 114.2 | 503.1 | 1.8 | 2 | 74D-R |
| 2.8 | 4.2 | 389.4 | 112.2 | 501.6 | 3.3 | 2 | 75D-R |
| 0.6 | 2.9 | 385.8 | 117.8 | 503.6 | 1.3 | 2 | 76D-R |
| 1.1 | 1.7 | 392.6 | 111.7 | 504.3 | 1.0 | 2 | 77D-R |
| 0.0 | 2.9 | 401.1 | 103.0 | 504.1 | 0.9 | 2 | 78D-R |
| 1.2 | 2.4 | 390.2 | 113.6 | 503.8 | 1.2 | 2 | 79D-R |
| 0.2 | 1.0 | 400.2 | 104.2 | 504.4 | 1.4 | 2 | 80D-R |
| 0.5 | 1.8 | 390.2 | 113.9 | 504.1 | 1.5 | 2 | 81D-R |
| 1.0 | 4.1 | 391.2 | 113.0 | 504.2 | 1.1 | 2 | 82D-R |
| 0.7 | 2.5 | 401.8 | 102.6 | 504.4 | 0.8 | 2 | 83D-R |

# APPENDIX C

# INSTITUTIONAL REVIEW BOARD APPROVAL

**OKLAHOMA STATE UNIVERSITY**
**INSTITUTIONAL REVIEW BOARD**

| | | | |
|---|---|---|---|
| Date: | June 24, 1999 | IRB #: | AG-99-034 |
| Proposal Title: | "REFINING THE US PEANUT GRADING SYSTEM" | | |
| Principal Investigator(s): | Wade Brorsen<br>Edgar Pebe Diaz | | |
| Reviewed and Processed as: | Exempt | | |

Approval Status Recommended by Reviewer(s): Approved

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(Secondary data)

Signature:

Carol Olson

Carol Olson, Director of University Research Compliance

June 24, 1999
Date

Approvals are valid for one calendar year, after which time a request for continuation must be submitted. Any modification to the research project approved by the IRB must be submitted for approval. Approved projects are subject to monitoring by the IRB. Expedited and exempt projects may be reviewed by the full Institutional Review Board.

2

**VITA**

Edgar F. Pebe Díaz

Candidate for the degree of

Doctor of Philosophy

Thesis: REFINING THE U.S. PEANUT GRADING SYSTEM

Major Field: Agricultural Economics

Biographical:

Personal Data: Born in Lima, Peru, February 26, 1961, the son of Fidel E. Pebe Falcón and Eulogia Díaz García. The father of Andrea Carol Pebe Bernal.

Education: Graduated from Colegio Nacional "José M. Eguren", Lima, Perú, in December 1976; received Bachelor of Science degree in Economics, Universidad Nacional Mayor de San Marcos, Lima, Perú in June 1985; Master of Science in Agricultural Economics at Oklahoma State University in Stillwater, Oklahoma in December 1996. Completed the requirements for the Doctor of Philosophy degree with a major in Agricultural Economics at Oklahoma State University in December, 1999.

Professional Experience: 12/85-3/87 Promoción y Capacitación de Adultos (PROCAD), conducted extension activities. 3/88-7/88 Asociación Civil Antisuyo, conducted economic research. 1/89-9/93 Centro de Apoyo y Promoción al Desarrollo Agrario (CAPRODA), conducted extension activities and economic research. 10/93-5/94 Consorcio de Instituciones Privadas de Desarrollo de la Región Arequipa (SURCO), conducted economic research. 7/94-6/95 Servicios Educativos, Promoción y Accion Rural (SEPAR), conducted extension activities and economic research. 01/97-10/99 Department of Agricultural Economics, Oklahoma State University, graduate research associate.

Professional Memberships: American Agricultural Economics Association (AAEA), Canadian Agricultural Economics Society (CAES), the Honor Societies of Gamma Sigma Delta and Phi Kappa Phi.