

COSTS AND RISKS OF TESTING AND BLENDING FOR EAA IN SOYBEANS

A Thesis
Submitted to the Graduate Faculty
of the
North Dakota State University
of Agriculture and Applied Science

By

David Jorgen Hertsgaard

In Partial Fulfillment of the Requirements
for the Degree of
MASTER OF SCIENCE

Major Department:
Agribusiness and Applied Economics

June 2015

Fargo, North Dakota

North Dakota State University
Graduate School

Title

Cost and Risks of Testing and Blending for EAA in Soybeans

By

David Jorgen Hertsgaard

The Supervisory Committee certifies that this *disquisition* complies with North Dakota State University's regulations and meets the accepted standards for the degree of

MASTER OF SCIENCE

SUPERVISORY COMMITTEE:

Dr. William Wilson

Chair

William Nganje

Ryan Larsen

Kim Koch

Approved:

6/12/2015

Date

William Nganje

Department Chair

ABSTRACT

Soybean quality is typically measured by protein values. Essential Amino Acids (EAA) and Critical Amino Acid Value (CAAV) provide alternative measures of valuing soybeans. The following thesis analyzes the effects of testing soybeans for specific quality traits. A dual-marketing system is developed to analyze the costs and risks that may arise for grain handlers to segregate soybeans into high-quality and low-quality grain flows based on various importer purchasing strategies. A stochastic optimization model is used to determine the optimal testing locations within the dual-marketing system in order to minimize costs and risks to grain handlers. The model includes a blending component to determine the optimal blending from different locations with various quality distributions. The thesis provides a framework for grain handlers to make decisions based on the international importers' various and numerous purchasing strategies.

ACKNOWLEDGMENTS

I would like to extend my thanks and gratitude to my adviser, Dr. William Wilson. His help, support, and guidance have been instrumental in the completion of my degree as well as my future and career within the agribusiness industry. I would also like to extend this sentiment to my committee members who have supported me: Dr. William Nganje, Dr. Ryan Larsen, and Dr. Kim Koch. The wisdom you have provided has been invaluable.

I would also like to thank members of the NDSU Agribusiness and Applied Economics department. The faculty and staff provided a high-quality environment for work and learning. I would also like to specifically thank Bruce Dahl for his expertise, knowledge, and guidance. His help was crucial in the composition of this thesis.

Finally, I would like to acknowledge my family and friends. The effort and support my parents have given over the past two years has been instrumental in the completion of this thesis and work. The same may be said of my close friends whose encouragement I value greatly. The close friendships that I have built in this department have been ones that I will never forget. I thank the people for what they helped me learn and what they taught me.

TABLE OF CONTENTS

ABSTRACT	iii
ACKNOWLEDGMENTS	iv
LIST OF TABLES	viii
LIST OF FIGURES	x
CHAPTER 1: STATEMENT OF THE PROBLEM	1
Introduction	1
Problem Statement and Objectives	4
Methods and Procedures.....	9
Organization	9
CHAPTER 2: REVIEW OF LITERATURE	11
Introduction	11
Protein and Animal Diets	11
Essential Amino Acids and Critical Amino Acid Value	12
Marketplace Incentives.....	17
Commodity Grain Merchandising	21
Spatial Flows	22
Contracts.....	24
Transaction-Cost Approach.....	25
Risks and Testing	28
Buyer and Seller Risk	31
CHAPTER 3: THEORETICAL FRAMEWORK	35
Introduction	35
Expected Utility Theory	36

Quality, Contracting, and Blending	39
Summary.....	43
CHAPTER 4: EMPIRICAL METHODS.....	45
Introduction	45
Testing Model Specifications.....	46
Testing Costs	50
Additional Model Costs.....	51
Requirements.....	53
Data.....	54
Distributions for Randomized Variables	56
Quality Distributions.....	59
Blending Model Description	59
Specified Model Cases	68
Case 1: No Testing	69
Case 2: Protein Testing	72
Case 3: Testing for Protein and Oil.....	73
Case 4: Testing for a Single Amino Acid.....	74
Case 5: Testing EAA.....	74
Case 6: Blending Model	75
Simulation and Optimization Procedures.....	80
Model Variable Distributions.....	80
CHAPTER 5: RESULTS AND ANALYSIS	82
Introduction	82
No Testing : Base Case.....	83
Testing for Protein	87

Testing for Protein and Oil	92
Testing for a Single EAA: Lysine.....	97
Testing for All EAAs.....	100
Testing and Blending Model	105
Strategy Summary.....	112
Summary.....	113
CHAPTER 6: CONCLUSION	117
Introduction	117
Problem and Objectives.....	117
Methodology and Model	122
Results Overview	125
Implications of the Study and Opportunities for Further Studies	129
REFERENCES	132

LIST OF TABLES

<u>Table</u>	<u>Page</u>
3.1. Risk Preferences	38
4.1. Model Costs and Parameters	52
4.2. Soybean Quality Requirements	54
4.3. Soybean-Sampling Data Summary	58
4.4. ND Quality Best Fit Distributions.....	60
4.5. North Dakota’s High-Quality Soybean Distributions	61
4.6. Nebraska’s Quality Distributions	66
4.7 Nebraska's High-Quality Soybean Distributions.....	67
4.8. Case Summarization.....	68
5.1. Base Case - No Testing.....	84
5.2. Base Cases – Not Testing: Probability of Meeting Requirements	85
5.3. Case 2 – Testing Protein: Optimal Testing Strategies	88
5.4. Case 2 – Testing Protein: Costs and Risks	89
5.5. Case 3 – Testing Protein and Oil: Optimal Testing Strategies	93
5.6. Case 3 – Testing Protein and Oil: Costs and Risks	94
5.7. Case 4 – Testing for a Single EAA: Optimal Testing Strategies	98
5.8. Case 4 – Testing for a Single EAA: Costs and Risks	99
5.9. Case 5 – Testing for All EAA: Optimal Testing Strategies.....	102
5.10. Case 5 – Testing for All EAAs: Costs and Risks	103
5.11. HQ Lots Meeting All EAA Requirements.....	105
5.12. Case 6 – Testing and Blending for EAA: Costs and Risks.....	107

5.13. Testing and Blending for All EAA	109
5.14. Strategy Summary: Costs and Risks	114
5.15. Strategy Summary: Optimal Strategies.....	115
6.1. Quality Variable's Summary Statistics	120
6.2. Quality Requirements (Merck Manuals, 2015)	124
6.3. Testing Based on Purchaser Requirements: Cases 1-5	126
6.4 Testing Based on Purchaser Requirements: Case 6	127

LIST OF FIGURES

<u>Figure</u>	<u>Page</u>
1.1. Protein Values (USSEC Data 2011-2013).....	4
1.2. CAAV Values (USSEC Soybean Quality Data 2011-2013).....	6
1.3. EAA Content Compared to Protein.....	7
2.1. Amino Acid and Soybean Quality by Origin	13
2.2. CAAV Compared to Crude Protein	15
2.3. (Gast, 2014 Soybean Meal Distribution)	19
2.4. (Gast, 2014) Soybean Meal Relative Values	20
2.5. (Wilson & Dahl, 2002) Grain Purchasing Quality Control Mechanisms	29
3.1. Total Quality Management, Optimal Quality with Costs (Porter & Rayner, 1992)	40
3.2. Total Quality Management of Buyer and Seller Risk (Porter and Rayner, 1992)	42
4.1. Dual-Marketing Testing Model	48
4.2. Dual-Marketing Testing Model with Blending Component.....	62
4.3. Model Specifications for Case 1.....	70
4.4. Model Specifications for Case 2.....	71
4.5. Model Specifications for Case 3.....	76
4.6. Model Specifications for Case 4.....	77
4.7. Model Specifications for Case 5.....	78
4.8. Model Specifications for Case 6.....	79
6.1. Protein Values (USSEC Data 2011-2013).....	118

CHAPTER 1: STATEMENT OF THE PROBLEM

Introduction

One of the unique qualities of soybeans is the level of proteins that they contain. Soybeans can be used as a feed source that only contains plant material and still provides enough protein for a diet. Many other meal sources require a supplement of animal-based proteins to reach desirable protein levels. A single source of protein and nutrition is more desirable than using multiple. In some instances, plant-based feed diets are supplemented with an animal feed source which contains a higher level of proteins. Because soybeans have the ability to provide this single source of protein, they are very sought after as a food source for livestock.

Proteins were identified in the mid-19th century and were described as “animal substances.” It was found that different feed sources provided better performance than others. This identification, in time, led to the discovery of amino acids which have been constituted as the building blocks of proteins (Gast, 2014). Further dietary studies with livestock showed that higher amino-acid concentrations led to better performance for livestock production. Protein levels were first tested through the amount of nitrogen that was in the protein. Later research determined, “It has become quite evident that the nutritive value of the proteins of feeding stuffs depends upon the quality and the quantity of the amino acids which compose the proteins and not upon the total nitrogen which they contain” (Grindley, 1917, p. 133). In the article, Grindley discusses that the measuring done while testing for just protein is “of little value and a very poor criterion for the purpose of estimating the true comparative nutritive values of the protein of different feeding stuffs” (Grindley, 1917, p. 133).

While protein is a close measure to the requirements needed by animals, it is not the substance that fuels growth. Proteins are merely the vehicle by which amino acids are delivered,

and amino acids are the building blocks of proteins (United States Soybean Export Council, 2013). It is the combination of amino acids and how they are comprised that gives us the protein composition. Protein values are important, but knowing the amino-acid content is much more important to understand the value of feedstuffs (Grindly, 1917). Further understanding amino acids has indicated that there are two classifications for them: essential and non-essential. Non-essential amino acids can be found in protein sources, but unlike essential amino acids, the organism does not have the ability to produce essential amino acids. This understanding of essential amino acids is the point at which amino acids entered into feed formulations. When an animal's diet is being formulated, it is important that the levels of essential amino acids are examined to ensure that proper growth levels are achieved.

Liebig's Law of Minimum states that the most available nutrient is only as good as the least available nutrient. By this law, the makeup of the essential amino acids is the most important factor when valuing feedstuffs. There are five amino acids that make up several universally "essential" amino acids. They are lysine, methionine, threonine, tryptophan, and cysteine (Naeve, Orf & Weidenbenner, 2013). Different animals require different essential amino acids, but these 5 essential amino acids (EAA) are most likely to be limiting and required by a variety of animals and diets. By quantifying and analyzing these five amino acids, a proper valuation of the soybean meal and soybeans may be applied.

One study highlighted the value of soybeans that originate in the United States. Maitri Thakur and Charles R. Hurburgh, 2007 tested and compared the quality of U.S. soybean meal to the rest of the world. What they found was a better source of proteins available for digestion. Their research indicated that U.S. soybean meal was, in fact, portraying a lower level of crude protein values when compared to that of meal from other origins. Compared to soybeans from

Brazil, U.S. soybeans exhibited both lower crude protein levels and lower levels of oil for extraction. However, the researchers also found that, for U.S.-grown soybeans, the meal produced had a much higher essential amino acid content. The authors also discovered that the deficiency for crude protein levels was offset by the high concentration of EAA. With a higher concentration of EAA, U.S. soybean meal held a distinct advantage over meal from other origins.

Over the past several decades, there has been a great deal of testing done to determine the nutritional value of soybeans and soybean meal originating from the United States and other locations around the world. The profile for soybeans grown in the United States has shown a uniformity of desirable traits that provides a “Total Value Package” (Naeve et al., 2013). There have been many feeding tests done to determine the value of soy meal, and throughout testing, conclusions about soybean quality have shown that U.S.-grown soybeans have

1. Superior amino-acid content and amino-acid profile
2. Increased metabolizable energy content due to higher sugar levels, lower fiber content, and improved amino-acid digestibility
3. Higher total phosphorus content
4. Greater uniformity of U.S. soybean meal among batches. These factors are all desirable traits that feed producers want for meal content and aid in the availability of amino acids.

These factors in turn, increase the value of meal and makes U.S. soy meal more appealing to livestock producers (Naeve et al., 2013).

For a long time, crude protein levels have been an easy way to measure the amount of protein in soybeans. Testing for crude protein levels is a traditional benchmark for the quality requirements and is used for contracting specific grades of soybeans. However, the levels of

crude protein do not completely define the soybeans' intrinsic value. While protein is a valuable measure of the potential growth in livestock, a diet based strictly on protein levels may lead to an inefficient feed schedule. Performance of the feedstuff is improved when low levels of crude protein are supplemented with amino acids. It is more efficient to use a soybean-meal source that is higher in protein quality with a balanced amino-acid level and a lower crude protein level than it is to use a higher protein, lower protein quality (unbalanced amino acids) level (Jeradechachai, 2012).

Problem Statement and Objectives

Concerns about soybean protein quality have evolved to become issues for producers and merchandisers in the northern Midwest region. The importance has become more apparent with the growth of soybean production in this region during recent years along with the more intense

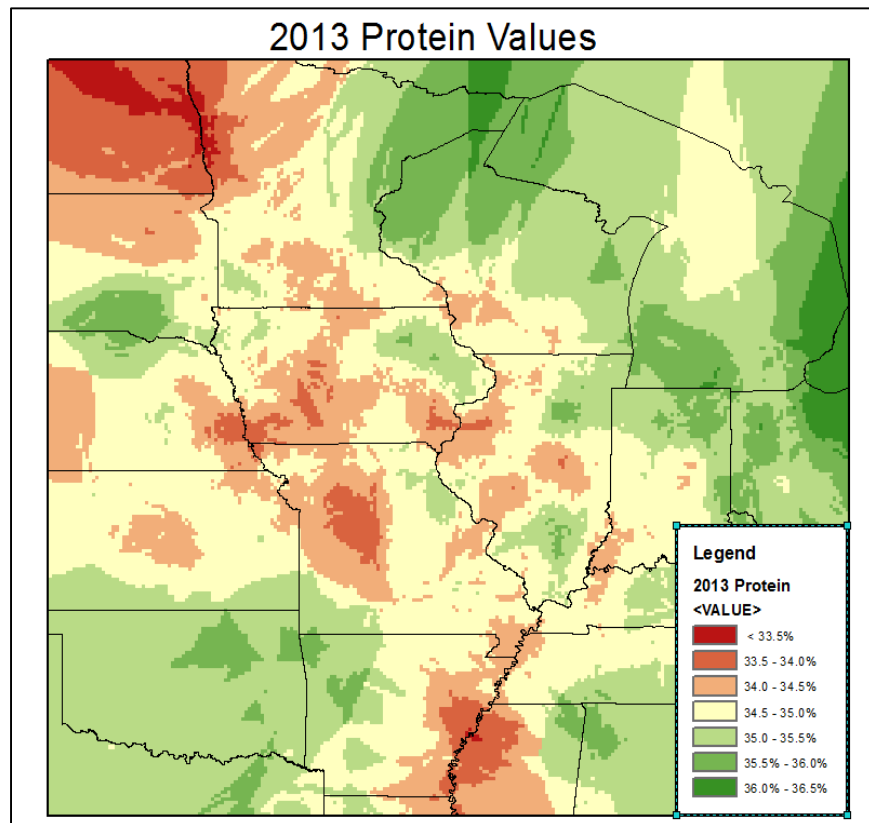


Figure 1.1. Protein Values (USSEC Data 2011-2013).

international and inter-regional competition for this crop. Soybeans grown in the northern Midwest typically have lower levels of protein compared to soybeans from other regions. This lack of protein is often due to impacts from spatially differentiated growing conditions. One of the major contributors for quality defects in North Dakota is the length of growing season and the amount of light that soybean plants receive. Due to the spatial variability for soybean quality, purchasers are inclined to discount or completely reject shipments from geographic regions with lower-quality levels, such as North Dakota. Figure 1.1 indicates the protein qualities and their spatial distributions. It is evident from the patterns that soybeans grown in North Dakota and other regions across the northern plains have lower protein qualities than soybeans from the southern regions.

Traditionally, soybean buyers prefer higher protein levels. Purchasing preferences can easily be measured in the market system, and implicitly, some buyers pay premiums for beans that meet the requirements. Beans that do not meet this specification may not receive this premium, or they may be subjected to discounts. North Dakota producers who grow higher-protein soybeans may see increased revenues of \$7.70 to \$12.96 per acre (United Soybean Board, 2015). However, there may also be negative outcomes for not meeting the specific protein requirements. Some buyers have refused to take shipment from Pacific Northwest (PNW) exports, presumably for this reason. Protein deficiencies also create a problem for producers in the northern Midwest because a large portion of the production is shipped to the PNW. Furthermore, the northern Midwest region's growers are at a disadvantage when competing with growers in regions where protein values are higher.

However, protein measurements do not tell the entire story regarding soybean quality. Soybeans are typically measured by the crude protein (CP) content which is determined by the

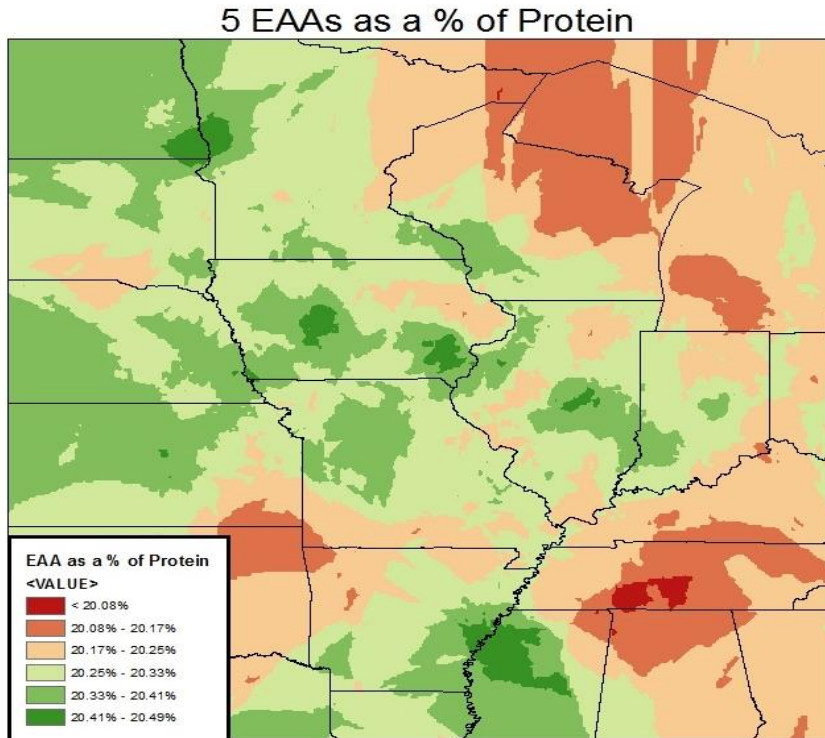


Figure 1.2. CAAV Values (USSEC Soybean Quality Data 2011-2013).

amount of nitrogen content within the soy meal. End users desire higher protein values due to the nutritional values when utilized as soybean meal for feed. When soybeans are purchased for protein, they are generally used for crushing and, eventually, as soybean-meal feed for livestock. Sophisticated livestock production has been aided by a feeding formulation where livestock producers aim to maximize growth based on feed inputs. However, feeding formulations are not based on protein values. Rather, the formulations aim to maximize nutritional value based on the amino acids that make up proteins. There are over 18 different amino acids found in proteins, however, there are only a handful of amino acids that are essential to aid livestock's growth. The five amino acids identified as essential to feeding formulations are cysteine, lysine, methionine, threonine, and tryptophan. These amino acids are known as the Essential Amino Acids (EAA). The problem is that the marketing system readily measures protein levels but not the elements of the EAAs. Using EAAs to measure soybean quality, rather than crude protein, may lead to new

assumptions and a better evaluation of soybean values. Valuing EAA rather than protein is important for soybeans grown in North Dakota, where the protein values are lower than other geographical regions. Figure 1.1 shows the differing quality levels for various regions. EAA analysis also provides additional insight about the quality of the proteins available in soybeans.

The Critical Amino Acid Value (CAAV) is a measure that simply takes the total amount of EAA and divides it by the total amount of protein available. Figure 1.2 shows the relationship between the CAAV and protein values. The table shows a decreasing relationship between CAAV and protein values. Thus, as protein values increase, CAAV decreases, meaning that the total concentration of EAAs decreases comparatively to soybeans with lower protein values. This relationship would imply that the EAA value decreases as the protein values increase. Figure 1.3 also indicates the CAAV's spatial conditions. It is evident that, where Figure 1.1 illustrated lower protein values, Figure 1.3 shows generally higher CAAV values. This evidence may lead to new ideas about the value of soybeans, protein, and EAA.

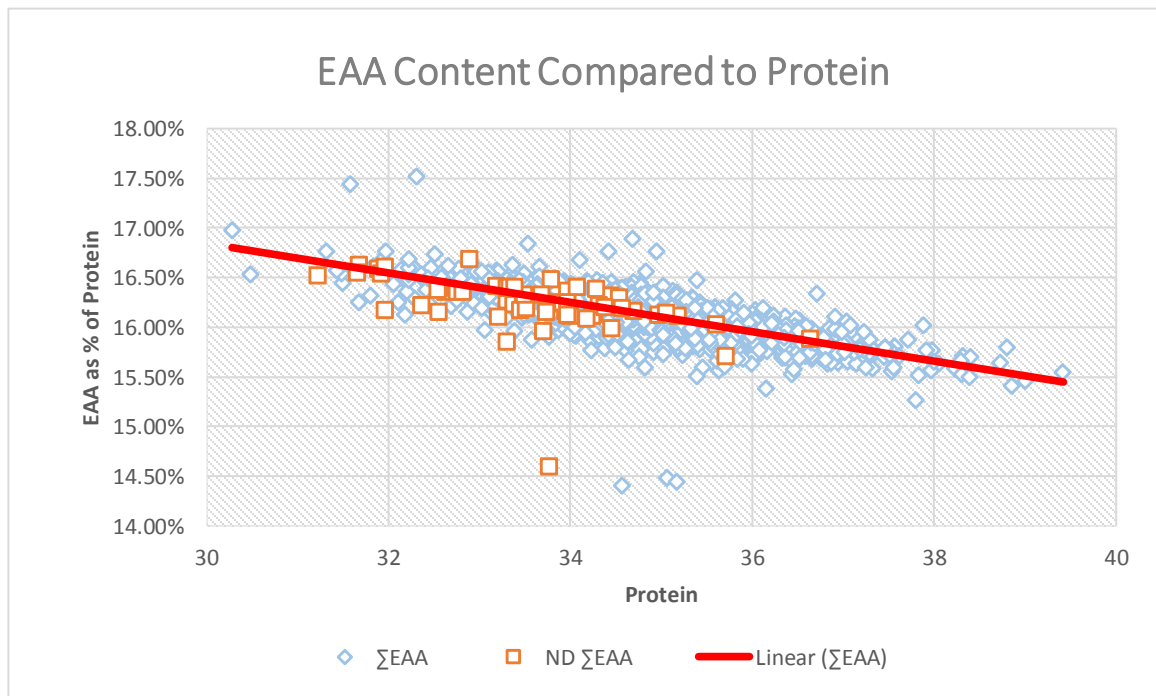


Figure 1.3. EAA Content Compared to Protein.

The overall objective of this study is to understand the impacts of quality requirements within the soybean marketing chain. Specific objectives include (1) What is the quality composition of spatially differentiated soybeans and the likelihood of meeting varying quality requirements? (2) What are the optimal testing and blending strategies that grain handlers should choose given the varying purchaser requirements and preferences? and (3) What costs and risks arise due to a segregated marketing chain?

Crude protein continues to measure the value of soybean quality in the marketplace. EAAs may offer an alternative to evaluate the soybeans' value. Analyzing the soybeans' quality characteristics allows for a greater understanding of the soybeans' inherent value. It is also important to understand the extra costs and risks that may arise due to the additional requirements, and the testing and operational procedures that may be required to determine and ensure soybean quality. One objective of this study is to analyze the additional costs and risks that grain handlers may face by taking part in a dual-marketing chain that tests and segregates soybeans based on different quality requirements. This analysis includes testing for protein, oil, and EAA. Purchasers may set requirements based on different quality measures, and the first portion of this study determines the impacts of testing. The second portion of this study aims to answer the question of optimal blending strategies. Blending two different lots with varying quality offers an additional alternative to ensure quality, limiting the variability and risks associated with quality uncertainty. Determining the impacts of blending to meet purchaser requirements is also a focus of the study. With multiple purchasing strategies available for a wide range of end-user preferences, meeting quality standards is costly and risky for grain handlers and producers. Analyzing these costs and risks is crucial for decision makers to operate

efficiently. The methods and modeling provided in this study measures the impacts for grain handlers as well as the optimal decisions when there are varying purchaser strategies.

Methods and Procedures

The purpose of this study is to determine the optimal strategies that soybean handlers would use for testing and blending soybeans to ensure quality. This study will also provide a better understanding of the costs and risks that may arise when incorporating a dual-marketing system. A model is presented in this thesis; the model mimics a soybean supply chain, from country elevator to export elevator and finally to an international importer. The model simulates the risks that grain handlers face due to testing errors as well as the other operational risks that may arise when handling heterogeneous segregated soybeans. Further, the model employs a disutility minimization that determines the optimal disutility based on the costs and risks incurred from the dual-marketing system.

Procedures involve @Risk software programming, where random parameter distributions incorporate the uncertainty of random variables into an optimization procedure. @Risk programming performs a stochastic optimization. Here, @Risk simulates 1,000 iterations over 1,000 simulations to search for the optimal solution in order to minimize disutility. Outputs of the testing strategies include mean outputs of the costs for the 1,000 iterations of the optimal decision.

Organization

This thesis includes six chapters. The first chapter introduces the topic, origination, and direction of the research. Chapter 2 features the background and intends to expand on the origination, while giving an in-depth look at the literature and research that has been conducted in previous studies. Chapter 3 introduces the methodology. The chapter will show the

generalized model. This chapter is a conceptual chapter and discusses the model's theories and implications. The empirical model is analyzed in Chapter 4. Here, the basic structure of the model is presented. There is an in-depth discussion about the model's details, and the actual simulation procedures are also addressed. The data set that will be used will also be discussed during this section. Chapter 5 is the results section. It is a general overview of the modeling results. The chapter also features a complete analysis of all models, including the base case, as well as any sensitivities that are conducted. Chapter 6 is a summary. It reviews the problems that were addressed and how the objectives were reached. Implications for the research are discussed along with how future studies may further this research.

CHAPTER 2: REVIEW OF LITERATURE

Introduction

The first section of the literature review focuses on the quality parameters of the soybeans' proteins and amino acids. The section also focuses on animal diets as well as the effects of soybean and soybean meal quality. For the purposes of this study, it is important to understand what effects animal diets have in soybean merchandising and contracting, which is also included in the review on literature. The following chapter focuses on contracting methods and testing strategies to minimize the risks associated with contracting strategies. Second, I discuss commodity markets as well as the dynamics for the risks faced by buyers and sellers in the market.

Protein and Animal Diets

Soybeans are a multipurpose crop. Generally, they are crushed and processed for two reasons: the applications of the oil and the leftover dry material, called meal, which is high in protein and provides energy as a feed. Due to this high value of protein Crude and nutrients, more buyers have been looking for ways to maximize soybean-meal content.

Crude protein has long been the measurement for soybean quality. Crude Protein has been the basis by which the nutritional component of soybeans has been valued, and it is the simplest means of determining the value as a feedstuff. It has been accepted by nearly all producers, processors, and merchandisers as a standard measure for quality. While crude protein does give some insight about the nutritional value of soybeans, it does not tell the entire story. Amino acids are the make-up of proteins, and their values tell a much clearer picture of the protein quality and how it affects the nutritional value of soybeans as a feedstuff.

The importance of amino acids is not a new concept, and the impact that they can have on growing livestock has been known for quite some time. In a study done by Grindley (1917), he discusses the findings that he and others found while running feed studies and analyzing the amino-acid content of soybean feed. The research shows several concepts. One is that protein levels can give an idea about the value in a feedstuff. However, using protein alone to determine value is a poor evaluation. While crude protein provides an idea about the protein quantity, it does little to tell us about the quality of the proteins themselves (Grindley, 1917). The second concept is that the quality and quantity of the amino acids are a better indicator for the value of soybeans and soybean meal. Many different amino acids are found in soybeans in various combinations and proportions. Overall, the value of soybeans is dependent on the balances and which amino acids would limit digestion due to deficiencies. Determining the value of soybeans and their subsequent feedstuffs requires knowledge about the overall protein as well as the availability of the limiting amino acids. It is important to have a balanced mix of feedstuffs to ensure proper nutrition (Grindley 1917).

Essential Amino Acids and Critical Amino Acid Value

Proteins contain many different types of amino acids. However, some amino acids are more important than others. Lysine, methionine, threonine, cysteine, and tryptophan have been identified as the most important amino acids for animal growth. These amino acids are generally the limiting factor for digestibility and have been termed the Essential Amino Acids (EAA) (Thakur and Hurburgh, 2007). Identification of these five EAAs is very important. The nutritional value of these amino acids is much more important for the feed formulation than other non-essential amino acids, and identifying the Essential Amino Acids aids in the construction of feed programs. Animal feed programs have been consistently improving over the last century,

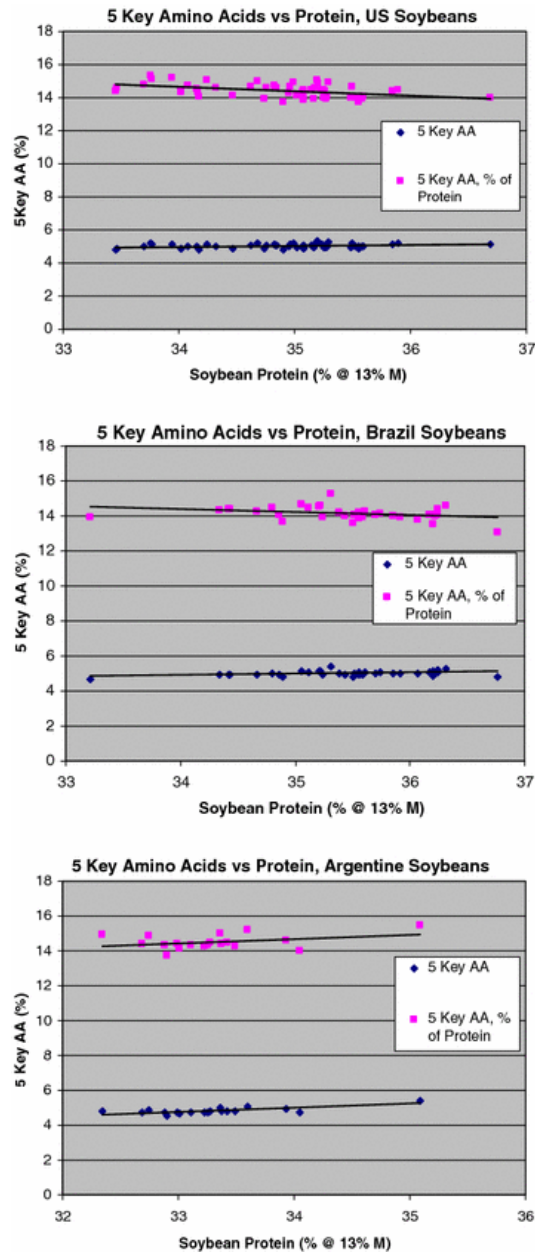


Figure 2.1. Amino Acid and Soybean Quality by Origin.

and mathematical modeling has aided in valuing the feed formulations. By understanding animal requirements for EAAs, feeding formulas can become more specific and efficient (Gast, 2014).

A study was conducted to analyze the quality differences between major export locations of both soybeans and soybean meal. This study was not the first research about soybean quality differences for various global origins. Thakur and Hurburgh 2007 used their analysis and compared the results to previous studies. The port of origin samples included Argentina, Brazil,

India, and the United States. Central American and Asian countries were also included in the study; countries at these origins were aggregated into two categories, others (Central America) and Asia. Measurements for the study included proteins, total amino-acid content, five EAAs, oil and free fatty acid (FFA) content. EAA is calculated by summing the values of all five EAAs. The Thakur and Hurburgh 2007 study focused on soybeans and soybean meal from both locations and compared samples to previous studies. A least-significant difference method was used to evaluate the profiles for the examples.

Results for the study showed interesting results when viewing the EAA content in comparison with the amount of protein in a sample. It was also noted that different locations resulted various EAA trends. Soybeans from the United States and Brazil indicated, that as the protein levels increased, the EAA concentration decreased (Thakur and Hurburgh, 2007). This relationship between protein and EAA indicates that, as protein levels increase, available EAA would decrease as a percentage of the protein levels; soybeans higher in protein had less available EAA per protein point. Differences for the EAA values are shown in Figure 2.1. It can be seen that the EAA content tends to decrease as the protein values increase. Note that this relationship is not true for soybeans originating from Argentina, suggesting that, while EAA content may tend to decrease as protein increases, there may be other geographical impacts that affect the protein and amino-acid content of soybeans. This geographic impact may be due to several different factors: (1) climate and the length of the growing season, (2) different weather for each growing season, (3) crop varieties and soil types, and (4) different agronomic practices (Naeve et al., 2014).

A point of interest is the function of amino acids and the term “EAA.” Essential amino acids provide nutritional support for growing animals, as discussed previously. The essential

amino acids are crucial for development in that they are indispensable, meaning that growth cannot occur unless the essential amino acids are present in the animal's diet. Furthermore, various essential amino acids are required for different species. For example, swine (monogastric animals) may only require 5-10 essential amino acids while poultry may require up to 12 essential amino acids. Differences in requirements creates a large amount of variation for the requirements and what is needed. Research presented by previous authors defines EAA as a five key amino acids. This term refers to the five amino acids that are most common across species and feeder preferences. The functionality of EAA is to define common, broad nutritional requirements as a marketing tool to more easily understand the impacts of amino-acid nutrition.

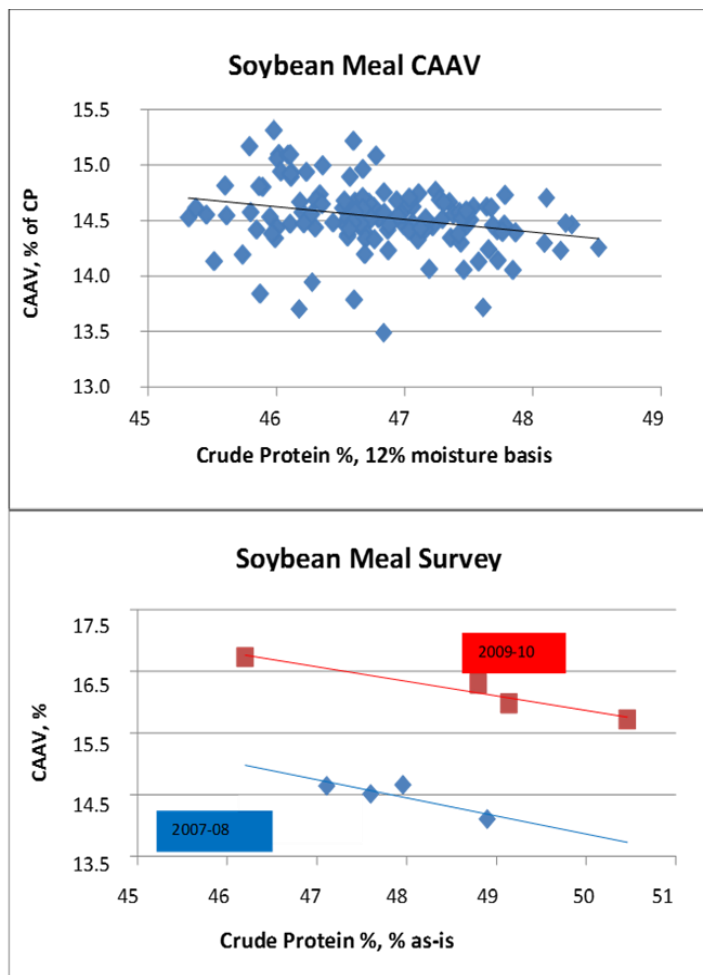


Figure 2.2. CAAV Compared to Crude Protein.

Further research (Gast, 2014) indicates similar results to that of Thakur and Hurburgh 2007. The study focuses on valuing the amino-acid content of soybeans and attempts to value soybean meal relative to its amino-acid content. The study uses soybean-meal samples taken from 63 northern and southern soybean-processing facilities in the United States. Here, there is an introduction of a new term, critical amino acid value (CAAV). CAAV is defined as “Expressing the sum of these five critical amino acids [lysine, methionine, threonine, tryptophan and cysteine], as a percentage of the crude protein, provides numeric value (CAAV = critical amino acid value) which provides an indication of protein quality and economic value in rations” (Gast, 2014, p.5). CAAV is crucial for understanding the economic value of protein qualities in soybeans as CAAV directly measures the relationship of EAA to protein levels in soybeans. Mathematically, CAAV can be expressed as follows:

$$CAAV = \frac{\sum EAA}{Protein \%} \quad (\text{Eq. 2.1})$$

Determining CAAV allows a single numerical representation to understand protein quality and provides a better measurement for the nutritional value in soybeans and soybean meal than simple protein measurements. Much like in the previous study, CAAV is shown to decrease as the amount of proteins increases. Figure 2.2 shows the level of CAAV as protein values increase.

Gast’s (2014) work has several different implications. First, defining CAAV allows for a simple, single measure by which to appropriately understand the value of protein quality compared to standard protein measurements. Second, CAAV has a similar trend to EAA in that it exhibits a decreasing value as protein levels increase. Third, using the feed studies, Gast was able to apply values to soybeans with different CAAV and protein values.

The quality of soybeans depends on a diverse set of characteristics. Generally, environmental conditions are the deciding factor that determines variable quality profiles. These conditions may include farming practices, the amount of sunlight (growing season and length of days), and different varieties affecting various quality standards. The quality of soybean meal is also thought to be contingent on crushing procedures and processes. The crushing process includes heating, cooling, and moisture levels. These different processes can affect the quality profiles of soybean meal (Thakur and Hurburgh, 2007).

The soybean crushing process is crucial to the quality of the soybean-meal output. Typically, crushing soybeans results in two outputs: soybean meal and soybean oil. The “crushing” process separates the oil from the dry soybean parts. The process begins by separating soybeans from the additional foreign material found in bulk shipments. The raw soybeans are then crushed into flakes by rollers. This process maximizes the surface area, so solvents may be introduced to pull the soybean oil from the crushed flake. When the oil and solvent have been removed, the resulting flakes may be further handled to create soybean meal. Further heating and grinding are applied to these soybean flakes to help with the digestibility for the proteins that the flakes contain (USSEC, 2008). The soybean meal that results from the crushing process contains varying nutritional values, based on the initial soybean quality, and varying crushing procedures. This meal is often used to blend with other feed sources due the high protein nature of soybean meal compared to other vegetative feed sources (USSEC, 2008).

Marketplace Incentives

Soybean quality has been lacking in standardized quality control when it comes to market valuation. The U.S. Standards Act grades soybean quality to qualify them, however, the process is not comprehensive testing and lacks some market-relevant aspects. The Federal Grain

Inspection Service (FGIS) oversees the grading of soybeans and marks the quality as 1, 2, 3, or 4 based on test weight, damaged kernels, foreign material, splits, coloring, and other material. Odor is also taken into account when grading (souring, molding, musty, etc). Moisture is not included when grading soybeans, but it is tested for and reported. Moisture content is important for the valuation of the sample's end use (USSEC Buyers Guide, 2015). Much like moisture, protein levels play a crucial role in the market and end-use valuation along with oil content. Protein and oil are also not included when grading soybean levels. However, many buyers expect certain levels of protein and oils when they purchase grains.

Sales contracts for exports to China show the quality requirements and that penalties are applied if the requirements are not met. Soybeans must meet the following requirements:

- U.S. No. 2 or better: must meet grading requirements
- Protein: 34.0% basis and 33.5% minimum
- Oil: 18.5% basis and 18% minimum

Penalties are listed for not meeting protein and oil levels. The penalties include a 1% price for protein levels between 34.0% and 33.5% as well as oil levels between 18.5% and 18%. Sales contracts specify that any levels below the minimum requirement may be rejected. While these requirements are specific to a single contract, other contracts contain similar verbiage. Contracts may differ based on the export destination or product source. The specified contract describes the terms of a sale from the PNW to China. In a similar marketing year, specifications for Indonesia and Taiwan require a full point higher for both protein and oil while Japan does not allow shipments from the PNW.

Further marketplace research has shown added value for soybeans with an increased value in protein. Livestock producers require a higher level of protein for production; their

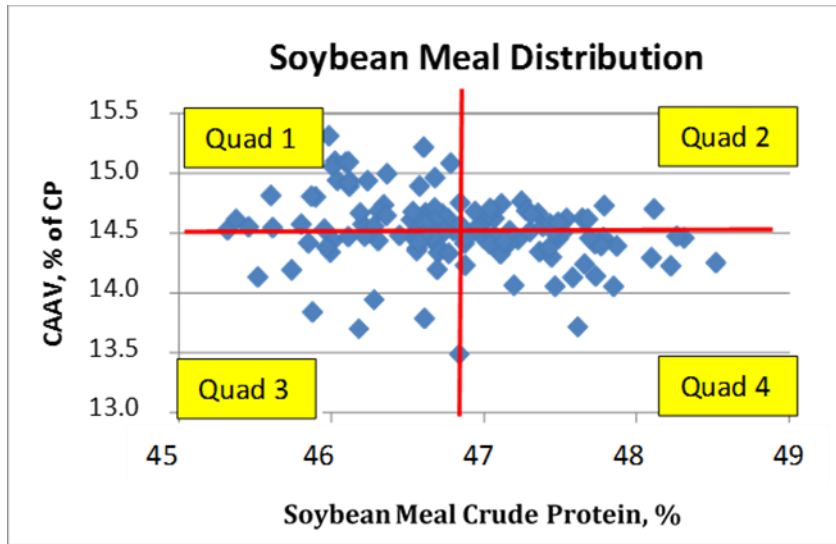


Figure 2.3. (Gast, 2014) Soybean Meal Distribution.

requirements create a market demand for higher protein content. According to studies conducted by the Centrec Consulting Group, LLC, farmers could see between a \$7.70 and \$12.96 increase per acre of soybeans. The per-acre increase for soybeans grown in North Dakota was estimated at \$10.81 (United Soybean Board, 2015).

Higher protein measurements may yield higher returns, but the same might also be said for CAAV. CAAV measurements and samples, coupled with the values derived from feeding formulations, offer value incentives for higher CAAV values. Figure 2.3 shows the value of all CAAV samples broken into four quadrants, separated by the median values of protein (X-axis) and CAAV (y-axis). The quadrants show low protein and high CAAV, high CAAV and high protein, low CAAV and low protein, and low CAAV and high protein (Gast, 2014).

Using the median values as differentiation between the high/low values and the feed-formulation models. Feed formulations are not based on a single ingredient variable; rather, there are many different aspects that go into creating an optimal feeding diet. Values are assigned to samples in relation to their CAAV content by using feeding formulas to break down CAAV samples into a nutrition-based formula based on purchaser preferences. The pricing is

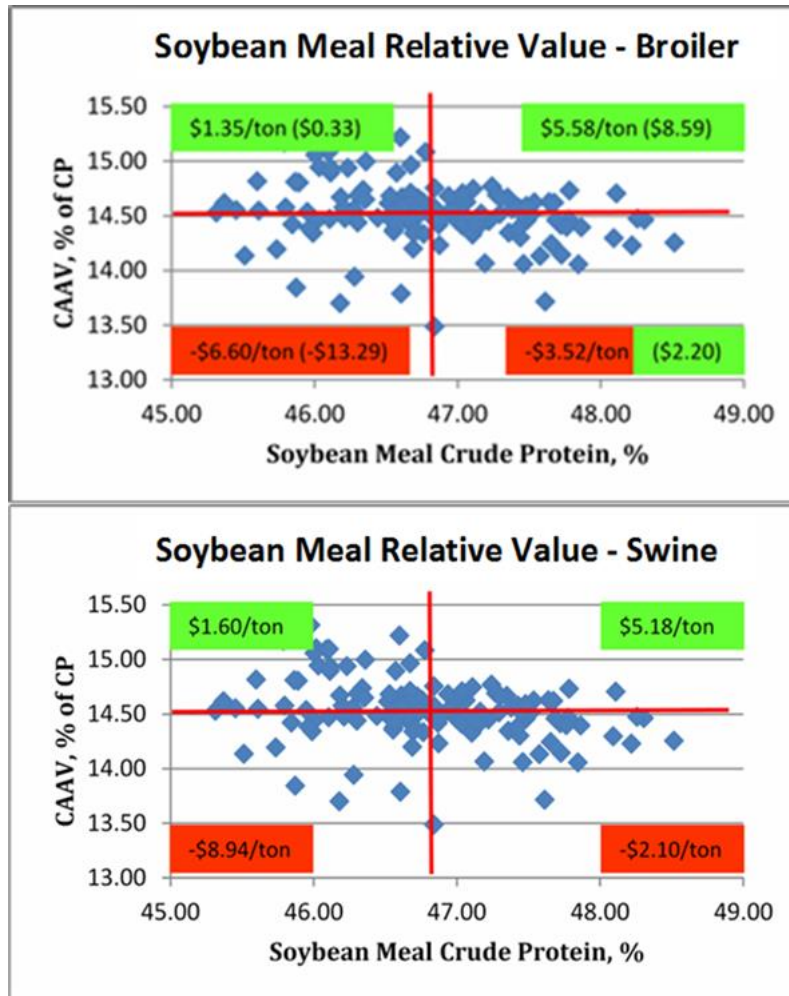


Figure 2.4. (Gast, 2014) Soybean Meal Relative Values.

determined by preference in both swine and broiler starter rations as shown in Figure 2.3 (Gast, 2014). This figure clearly shows that a higher CAAV increases the soybean meal's value while a higher level protein meal also needs to have a higher level of CAAV to ensure increase value. The study is able to successfully apply economic values to soybeans based on different quality traits as shown in Figure 2.4. However, the study does not address how CAAV may be implied for daily trading of soybeans or soybean meal. Traders are interested in a simple, basic evaluation of quality as well as other characteristics. Crude protein levels have been the standard for soybean and soybean meal trading. There is a great deal of room for further work.

Commodity Grain Merchandising

The volatility of grain markets creates risk in a variety of ways. Merchandisers who buy, sell, and handle grain are exposed to this risk. Over the last decade, there has been a vast increase in the amount of risk that people in the grain-marketing chain face. The risk and volatility lead producers and marketers to look for ways to alleviate risks through crop-marketing practices. Industry changes lead to new opportunities and risks for all involved with marketing grain.

Structural changes to the market have affected the way grain handlers operate. In a 1999 study, Wilson and Dahl outline structural changes in the industry that have most affected the markets. Firm privatization has played a crucial role in altering the demand in the marketplace along with the channel of influence. With importers acting as private buyers, rather than nationalized purchasing organizations, more specific demands may be required from international producers. This specificity for trade is likely to come in the form of quality specifications. With a channel of influence altered, private buyers have a chance to exercise their quality-specific preference and pass it along to originators and producers.

The composition of firms towards a more vertically integrated style has supported this trend. Companies have moved from a disintegrated group of buyers to a more vertically aligned structure. Vertical alignment has been a result of both mergers and acquisitions for firms in the market along with joint ventures. Vertical integration allows for a more streamlined supply chain system so that end users have a closer and more responsive connection to producers (MacDonald et al, 2004). Vertical integration has allowed for:

1. Economies of transportation, handling, and related demands;
2. Quality control; and

3. Strategic changes to mitigate the market power of firms elsewhere in the vertical market system (Wilson & Dahl, 1999).

Overall, vertical integration gives international buyers greater access to originators and specifications of their imports.

Spatial Flows

Arbitrage is a major determinant of the spatial flows in commodity markets. It allows for purchasers of homogenous products to take advantage of price disparities at different geographical locations. Arbitrage can be defined as the simultaneous purchase of a product in one market and the sale of that same product, in a separate market, at a higher price for a profit. By this theory, if price disparities arise with inter-regional markets, a commodity's spatial flows may change in order to adjust to arbitrage opportunities. This concept may be understood further with the law of one price. In spatial markets, the law of one price supposes that prices for a homogenous commodity should differ by no more than the transportation and transfer costs (Goodwin et al., 2011). If the price difference between the two markets is greater than these costs, arbitragers will take advantage, and the prices should be equal, less the transport and transfer costs.

Arbitrage helps to enforce the law of one price, however, this convergence of prices is not the case in reality, and even though arbitrage opportunities exist, barriers may exist, preventing arbitrage from taking place. New costs and risks arise when taking advantage of arbitrage opportunities. Beyond transfer costs, there are other barriers that may inhibit trade flows between two different regions. Government policies and transportation infrastructure affect buyers' ability to effectively arbitrage. In 2011, prices between Brent and West Texas Intermediate (WTI) for crude oil diverged due to a large supply increase from more oil

production in North Dakota and Canada. This large supply increase from the Midwest lowered prices of WTI crude oil while Brent crude, priced near the Gulf Coast port, decreased (Borstein and Kellogg, 2012). Given the arbitrage opportunity, these prices should have converged. However, price convergence was not the case. The lack of convergence was thought to be a result of a bottleneck of flows. Pipelines, the main method of oil transportation, were not able to move to regions with price disparities. The study showed the effects that infrastructure can have on arbitrage opportunities.

Theoretically, arbitrage is thought to be riskless, however risks do emerge in the form of basis, transportation costs, and quality (Skadberg, 2014). International purchasing agents have been enhancing their sophistication and specificity during the last several decades. Quality plays a role in the specifications for which purchasers are interested. Furthermore, quality may play a role in the spatial flows that affect commodities. What little information we may have about contract specifications shows the affects that lower quality may have on spatial flows. For instance, sales contracts from Japan specify that soybeans shipped from the PNW will not be taken by buyers. This origination restriction has several implications: (1) costs may be incurred if shipments are rejected, and (2) procurement and sales become restricted geographically by buyers and sellers. Furthermore, purchasers may be inclined to purchase from regions where certain qualities may be more prevalent. For instance, in the case of soybeans, Brazil shows trends of having higher protein levels when compared to other origins across the globe (Thakur and Hurburgh, 2007). This trend has implications for purchasers who aim to acquire soybeans with higher protein levels because buyers may have a preference for a higher protein soybean. This preference may cause a shift in trade flows because the demand for Brazilian soybeans may shift from areas that do not fit the same protein profile as Brazilian soybeans. Reasons for

differing quality factors can stretch a broad spectrum. Geographically, producers may encounter different growing conditions, different varieties, or different handling systems that may alter the quality and content.

Specific qualities may not be abundant in resources. Purchasers strategize, appropriately, in order to assure that they not only realize the most cost-effective strategy, but also to ensure that the produce quality of purchases is adequate. More specific purchasing pushes buyers to move from a least-cost purchasing strategy (Johnson et. al, 2001). Higher procurement costs may result in more risk for purchasers. Because spatial flows are affected and risks are increased, purchasers are interested in alternative ways of reducing risk. Contracts with higher specification levels are increasing and provide a means to lower purchasers' risk.

Contracts

Grain marketing of large-scale commodities has typically been defined by price and quantity. With a greater need for specified quality traits, more descriptive parameters for quality need to be outlined. Contracts offer a way to mitigate the price risks faced in the market as well as to offer opportunities for producers and buyers to specify quality traits (Sykuta and Parcell, 2003). Building on the previous work shown here, vertical integration has led to the role that contracts play in the supply chain. Vertical integration allows for better coordination between producers/originators and end users; this offers greater vertical coordination by specifying contract terms and leads to a more sophisticated procurement (MacDonald et al., 2004).

Contracting is used as a method to share risks and operates with three motivators: (1) grain handlers are exposed to risk; (2) many grain handlers are risk-averse and are willing to pay to reduce risks; and (3) grain handlers' exposure to risk can often be reduced, thereby creating a market for risk reduction (MacDonald et al., 2004). Both parties, the buyer and seller, are

exposed to risk, and through contracts and similar methods, buyers and sellers are able to pass some of the risk to parties who are more willing to handle it. Typically, buyers are better able to handle risk than farmers. This is due to the fact that buyers are more diversified in their products and have different regions from which to acquire a product. Diversification does not mean that buyers are more risk averse but, rather, that they have more practices that allow for risk removal.

Transaction-Cost Approach

The purpose of this study is to determine new methods of testing and to evaluate the contracting concerns for EAA and CAAV measures in soybeans. The intent is to understand the effect that testing may have on spatial flows for the commodity. However, these testing and contract strategies open producers and purchasers to new costs. As noted earlier, arbitrage opportunities must have enough economic incentives to overcome the costs that may arise with each opportunity. The transaction-cost approach investigates the effect of increased costs between buyers and sellers as well as how it affects these relationships.

Transaction costs are a critical focus of new institutional economics. Transaction costs have opened the door of opportunity to those in advantageous positions of vertical integration and have allowed for opportunistic behavior. This opportunity bears a problem for those who have no such advantage of economies. While vertical integration is one way for people to overcome these costs, governing structures, in the form of contracts, serve as a means for individuals who are susceptible to risks from transaction costs.

Transactions contain three critical dimensions: (1) uncertainty, (2) the frequency with which transactions recur, and (3) the degree to which durable transaction-specific investments are incurred, with uncertainty being the most important of the three (Williamson, 1979).

Transactions costs play a determining factor in relation to incentivizing contracts, which is also

true of specialized assets (transaction specific). On the other hand, specialized assets have a much lower hazard level. Both suppliers and buyers may turn to other alternative sources for a purchase and sale. Transaction-specific assets have less adaptability in the marketplace for both the buyer and seller; therefore, both have an incentive to execute for mutual benefit. This benefit increases over time because adjustments for execution inefficiencies may occur early, leading to previous thoughts; because suppliers and buyers are reliant on each other for transaction-specific assets, they are incentivized to invest in specialized equipment/plants (Williamson, 1979). In the realm of this study, these equipment/plants may be viewed as testing for specialized quality traits. Because the buyer and seller both stand to gain from developing higher-quality soybean traits, both of them may be incentivized to supply capital for testing systems and the contract costs that would ensue. Higher quality would create a system of profit maximization for buyers and sellers.

Contracts may be used as a method to further specific trade requirements by inducing incentives to employ relationship-specific investments. Chung (1991) determines the effects that contracts may pose on the buyer/seller relationships. One argument made is that renegotiation and/or revision of initial agreements may be a simple way to balance the incongruities that occur after delivery due to the uncertainty posed at the point of a contract agreement. If both buyers and sellers are incentivized to invest in a means to correct ex-post inefficiencies, both parties may benefit from such contract terms. Agreed-upon terms have one of two bargaining options (take them or leave them) at the time of delivery for both the buyer and the seller. Chung creates a procurement model based on payoff functions for buyers and sellers that is specified as follows:

$$\text{Seller Payoff: } t - c(q, w, \sigma) - h_s(\sigma) \quad (\text{Eq. 2.2})$$

$$\text{Buyer Payoff: } v(q, w, \beta) - h_b(\beta), \quad (\text{Eq. 2.3})$$

where q is the quantity of goods and t the monetary transfer from the buyer to the seller. W is the random variable reflecting the exogenous uncertainty which affect both the buyer of having goods and the seller's cost to produce the goods. σ and β represent the seller and buyer's investment cost, respectively. $h_s(\sigma)$ is the direct cost to sellers for making σ units of investments, and $h_b(\beta)$ is the same for the buyer. Furthermore, a contract-optimization model is presented, where U^0 represents the utility of the buyer in this case.

$$\text{maximize } \int [v(q, w, \beta) - t - h_b(\beta)] dF(w) \quad (\text{Eq. 2.4})$$

$$\text{subject to } \int [t - c(q, w, \sigma) - h_s(\sigma)] dF(w) \geq U^0 \quad (\text{Eq. 2.5})$$

Contingent on assumptions, both parties will agree to investment costs at (β^*, σ^*) , representing the maximized net gains from the investments. Assumptions of this dictate that both buyers and sellers are risk neutral. However, Chung (1991) includes an analysis of a risk-sharing contract. In a second proposition, he outlines two different circumstances where optimal contracts can be devised to induce investment: (1) is if the risk-averse party does not face uncertainty or (2) if the risk-averse party does not need to make an investment:

$$(1) \ c(q, w, \sigma) \text{ is independent in } w. \quad (\text{Eq. 2.6})$$

$$(2) \ c(q, w, \sigma) \text{ is independent in } \sigma \text{ (or } \sigma^* = 0) \quad (\text{Eq. 2.7})$$

In conclusion, it was discovered that optimal contracts may be written to induce investments for contract specifications. While assumptions of risk neutrality create the best model options, risk aversion may also be the best option if certain assumptions concerning the parties' risk proclivity are met.

Risks and Testing

In the case of amino acids, there are two different tests to sample and estimate the value of the soybeans' amino-acid content. A wet testing method can be used to examine the soybeans' content and quality. The method is generally an intensive procedure that takes a great deal of time and money. While wet testing gives the best estimates of soybean contents, it is not practical economically for testing large shipments. Another alternative is near-infrared spectroscopy (NIR). NIR would be the preferred testing method because it is more cost effective. Application of the test is becoming more accurate, and some importers have started accepting it when inspecting shipments.

Overall, there is a lack of studies about the markets for higher-quality soybeans, specifically with regards to testing and contracting. Market players do have an interest in quality, as shown earlier. This includes specification of protein and their limits. Quality specification creates demand and incentives for producers and marketers to create incentives for contracts that channel appropriate quality-grade products to the end users, in this case oversea processors. Desire for increased quality naturally creates risk in several different forms. These risks, in turn, generate costs during the transactions. Grain handlers face many different types of risk. These risks may be in the form of price risk, buyer and seller risk, and risks resulting from testing.

Studying quality attributes of commodities requires a look into the supply chain analyzing events of transfer and which events cause costs. These points not only offer costs, but also opportunity for quality preservation and identification. Wilson and Dahl (2002) studied the costs and risks that came about as a result of the marketing agents testing and segregating genetically modified wheat. Wilson and Dahl (2002) determined a system that devised optimal testing locations to minimize costs from testing, rejecting, and/or discounting. The study is

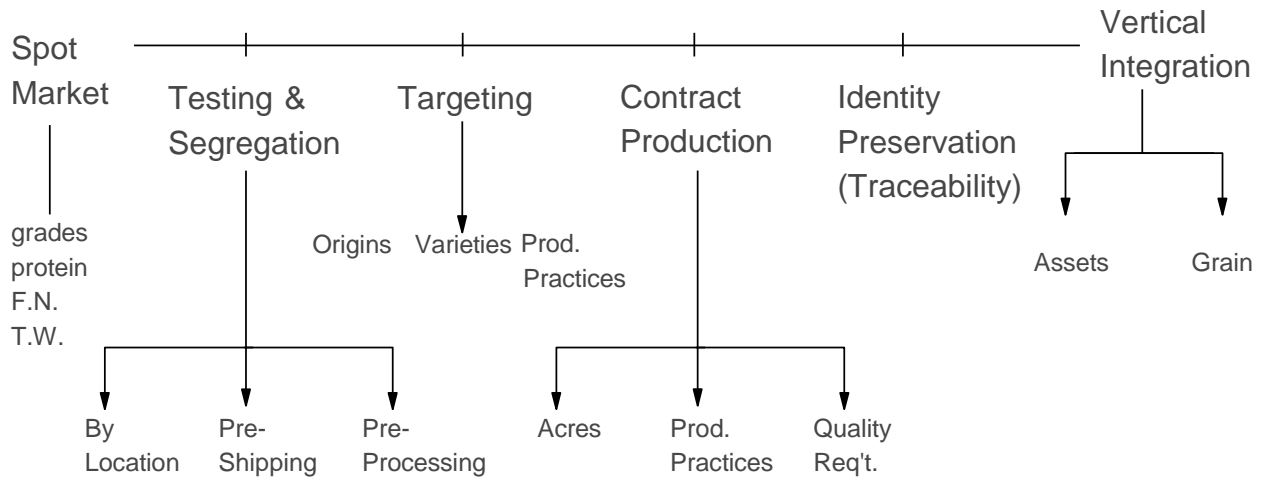


Figure 2.5. (Wilson & Dahl, 2002) Grain Purchasing Quality Control Mechanisms.

prefaced with an understanding of quality and testing within the supply chain and is as it appears in Figure 2.5.

As discussed earlier, spot markets do have grading factors of protein, however, it has been shown that those factors appear to be inefficient when determining the economic value of soybean content. Rather, CAAV may be a more appropriate measure. Spot markets do not have means or measures by which they can value CAAV. Rather, alternative measures of testing and segregating soybeans may be included when contracting for specific CAAV traits. As seen in figure 2.5, testing may occur at handling locations: pre-shipping and pre-processing. Many international purchasers have begun testing for amino-acid content at processing locations. Unfortunately, testing has not filtered down the supply chain, which is much of the implication for this study. Testing allows handlers to with minimal levels of risk throughout the supply chain (Wilson and Dahl, 2002).

While ensuring knowledge about grain quality, testing is imperfect and does create some risk levels. Testing accuracy depends on different factors from technology accuracy to the tolerance and frequency of testing. Risks associated with testing the quality levels may be

mitigated and quantified with appropriate testing strategies. By understanding the testing mechanisms used, handlers can assess their levels of risk and exposure due to testing. In their study, Wilson and Dahl (2002) determined the optimal testing strategies to ensure minimum risk. Naturally, more stringent testing will ensure a higher, more consistent quality level. However, more testing would generally include a higher cost which may not outweigh the premiums or (dis)incentives offered. More stringent testing would lead to more rejected deliveries, adding protection for buyers. Testing would leave sellers open to more risk because the parameters would be much more difficult to reach (Sykura and Parcell, 2003).

Changes in grain-marketing strategies have altered how merchandisers buy and sell their grain; more merchandisers make purchases based on specific quality factors. Therefore, quality specifications are becoming more prevalent in the market. Emphasis of quality has led to an analysis of quality, requirements, and testing strategies. Several previous studies have been conducted to analyze quality factors along with other topics surrounding marketers' responses to purchasing based on quality. In 2001, Johnson et al. conducted a study that analyzed the effects of vomitoxin in spring wheat. Vomitoxin is a natural, negative byproduct in wheat, and vomitoxin varies depending on the growing and/or production conditions as well as other factors. Vomitoxin adds a negative benefit to spring wheat. The goal was to analyze the risk and uncertainty of vomitoxin in spring wheat as well as the procurement strategies that might be used to combat these risks.

Johnson et al. (2001) proposed a mathematical model that found a maximal revenue function to determine optimal sales revenue while being constrained for grain availability and quality requirements. The study posed that quality is subject to the variability and risks from inaccurate testing. A failure to meet specifications resulted in discounts and a loss of revenue

from discounts or other shipping costs to alternate buyers (buyers with less-stringent specifications about vomitoxin). Testing failures put buyers and sellers at risk for misrepresented grain shipments. Further discussion of buyer and seller risk will be in the next section.

Vomitoxin limits were based on purchaser preferences, and distributions were taken from wheat samples from different regions because the growing conditions play a determining role for quality levels. Transportation costs were also used and helped to determine the purchasers' spatially optimal procurement strategies (Johnson et al., 2001).

With a specified model, the results showed the maximum revenue based on spatial flows of grains with varying vomitoxin levels and the appropriate discounts to incentivize shipments. The availability of grain was also a factor to determine flows. The study had three findings for its base case: (1) spatial flows were constrained to three different markets: U.S. milling, PNW other, and PNW Korea; (2) increases for the mean and variance of the vomitoxin levels had a negative effect on prices; and (3) procurement strategies were reflected in the contracts and affected buyers' competition based on regions. The size of premiums and discounts were important to determine spatial flows. Sensitivities were also conducted to determine additional effects. The study found that increased mean values and variances for the vomitoxin levels greatly affected how buyers' strategies would differ in these situations, which is of great value to producers and their perception of market-price signals from premiums and discounts. These procurement strategies are key factors to determine competition among buyers (Johnson et al., 2001).

Buyer and Seller Risk

This study considers the risks of testing for quality variables in soybeans. To determine risks of testing, contracts are utilized to develop a plan for testing shipments at the transaction points. Random sampling from a hypogeometric distribution can give an idea about the risks that

both buyers and sellers are subject to when they enter a contract. Buyer risk is the risk that purchasers face when shipments that do not meet specification requirements are actually accepted. Conversely, seller risk is the risk that sellers face when a shipment meets the specification requirements but is rejected. Furthermore, these specifications may be defined as the lot tolerance percent defective (LTPD) for the seller and the acceptable quality level (AQL) for the buyer (Winston, 2001). In either case, both the buyer and seller are subject to inaccuracies of sampling shipments, which cause either a loss of value from a shipment defined as acceptable quality (buyer) or a loss of sales value due to the quality not being met (seller). When hypergeometric distributions are applied with sampling plans, contracts may be devised to minimize risks for both parties to an agreeable degree. The theory for this testing and distribution is discussed further in Chapters 3 and 4.

This concept has been used to analyze the risks that buyers and sellers face due to quality standards. Wilson and Dahl (2003) analyzed the impacts of testing and segregation as they relate to genetically modified (GM) wheat. The study's purpose was to determine the optimal testing strategies to quantify the costs and risks for such a system. Adopting GM wheat creates new markets because buyers may prefer non-GM wheat compared to GM wheat. Preferences for non-GM wheat included a need for identity preservation and testing to prevent adventitious commingling and to mitigate testing risks. Using a stochastic optimization model, Wilson et. al (2003) found optimal testing locations that would analyze the system's costs and risks, determining the risk premiums necessary to induce investments in such a system.

A dual-marketing system is required for the analysis because adventitious commingling is an issue throughout the supply chain. However, a dual marketing system could result in non-GM wheat being exposed to GM wheat, negatively affecting the lot's testing. The risk of

adventitious commingling requires testing throughout the supply chain to ensure quality and segregation of the two states. Much like Johnson's study (2001), buyers and sellers are subject to similar risks of testing rejection. To overcome these costs and risks, premiums must be offered.

Wilson et. al (2006) offers a risk premium as a part of the analysis. The risk premiums represent the point at which the decision makers would be indifferent to using traditional non-GM systems or utilizing a dual-handling system that includes both GM and non-GM wheat. The dual-handling system is used in the stochastic optimization model in the form of a utility function to maximize utility by minimizing the costs represented by the two states, GM and non-GM wheat. Distributions are taken from testing the risks based on the levels of commingling risks for the two states. Distributions represent the risks of a batch meeting or not meeting certain requirements. The model is designed to designate when to test and what risk premiums are needed for decision makers to be indifferent about which system to use.

The model was run for several different cases with different sensitivities. The initial base-case results showed that the testing strategy should examine every fifth load at the country elevator along with testing every unit at the export elevator. It was also found that a risk premium of 96 cents/bu would be incurred. This cost represented the implicit cost accrued by the shipper to be indifferent for either a GM or non-GM system. Sensitivities for this test were conducted with several different variables, including the risk preferences for the risk handlers, and the costs of testing and rejection. Increasing risk aversion elevated the risk premium required but did not alter the optimal testing strategy. Decreasing risk preference lowered the amount of testing needed and lowered the overall system costs.

These findings had several different implications: (1) a testing system can ensure GM buyers with acceptable quality at a reasonable cost; (2) systems that use risk premiums can have

much less cost than other identity-preservation systems; (3) there are many factors that will affect the elements of an optimal testing system; and (4) strict interpretation of the risk premium would indicate that this premium is required to induce a dual-marketing system for GM and non-GM wheat. All of these findings implied that a system could be used to require contract mechanisms in order to control the systems' costs and risks.

CHAPTER 3: THEORETICAL FRAMEWORK

Introduction

Agricultural industries are naturally exposed to many different types of risk. Price, yield, and quality all cause uncertainty for farmers, grain handlers, and processors. Monte Carlo simulation can be used to identify and quantify the risks that may arise in many different situations. In a dual-marketing chain, handlers are exposed to risks from adventitious comingling and testing errors. Dual-marketing chains also have the decision to test for different quality traits at each level. Testing not only incurs costs, but also adds other risks for handlers. Given the additional costs and risks, grain handlers may expect to have a higher or lower expected utility. This expected utility from incorporating a dual-marketing chain provides a method to quantify the costs and risks that may arise due to testing. In the expected utility framework, the grain handlers' risk preference structure implies a set of restrictions for optimal responses to changes in price, income, cost, and risk (Saha, 1993). A flexible form for expected risk utility may be used in order to adhere to different assumptions for the risk preferences. Beyond understanding risk preferences, optimization may be used for best-case testing strategies. Other implications of determining the optimal testing strategies extend to risks premiums, where the expected utility of a given strategy may quantify the additional value needed for grain handlers to take part in a dual-marketing supply chain and to incur greater risks.

Quality of commodities plays a role in risk practices and determining the market value. Nearly every decision to produce, buy, or sell is influenced by a product's quality. The quality is a key competitive component with which all market participants have to deal. However, it can be costly and risky to search for and determine quality. Measuring quality may be necessary because markets change and adapt to new demands for quality specifications (Browbrick, 1992).

Adaptations for supply chains and marketing systems may provide a more assured quality level. Testing, segregation, blending, and other methods may be useful to improve the quality and value of grain-marketing models.

This chapter presents the Theoretical Framework that is the basis for the model. It is organized as follows. The first section presents the Expected Utility Theory and how individuals manage risk and make decisions. This section includes a discussion about risk preference and various risk attitudes. Generalized models of expected utility are presented as well as a discussion about the risk premium. After expected utility, the theory of quality in markets is presented. This section includes the market impacts of identifying, segregating, and blending grain.

Expected Utility Theory

The expected utility function, known as the von Neumann-Morgenstern utility, identifies the economic behavior of individuals or firms under uncertainty (Nicholson and Snyder, 2008). Expected utility allows for individuals to assess risk situations in order to determine which one is preferential when outcomes are uncertain. Expected utility assumes that individuals, when evaluating different risk situations, substitute wealth values with monetary values for the utility of wealth (Serrao and Coelho, 2000). Utility of wealth allows for individuals to assess the investment for a particular decision. Furthermore, it is assumed that decision makers are inclined to seek maximum utility, meaning that, for a set of decisions and corresponding risk factors, individuals will choose the set of decisions that maximize utility.

Extending this concept to grain handling can help to illuminate this idea. For example, take the case of a grain handler who wishes to test for differing qualities where each quality has a differing value (assuming a higher quality is of higher value). Testing offers a more secure way

to manage quality risk levels; the more frequent and intense testing offers a greater probability for getting higher-quality grain. However, wealth decreases as costs increase, reducing wealth and expected utility. Additionally, less and lower testing intensity decreases the probability of higher-quality grains. Seeking to maximize the expected utility, the grain handler would choose a testing option that returns the highest expected utility, such that the probabilities are higher to secure higher-quality grain while minimizing costs.

While individuals are inclined to maximize utility, they may turn down decisions that result in higher risk factors. This concept would indicate that decision makers are risk averse. Nicholson and Snyder (2008) define a decision maker as risk averse if he/she always refuses fair bet. If individuals exhibit a diminishing marginal utility of wealth, they are risk averse. As a consequence, they are willing to pay something to avoid taking fair bets (Nicholson and Snyder, 2008). Take an example of two decisions with similar expected-utility outcomes. The first one has a lower level of variability and risk for while the second one has a higher level of variability and risk. The first decision would be preferred because it offers a smaller variability of return. Some structures of risk aversion imply that decision makers are inclined to avoid risk for a more certain outcome. Not all assumptions about risk preference lead to an assumption of diminishing marginal utility. There are several different forms of risk aversion, including decreasing absolute risk aversion (DARA), constant absolute risk aversion (CARA), and constant relative risk aversion (CRRA; Saha, 1993). Saha (1993) presents a functional form of utility that exhibits both relative and absolute risk aversion in the form of the expo-power utility function defined as follows:

$$u(w) = \theta - \exp\{-\beta w^\alpha\}, \quad (\text{Eq. 3.1})$$

Table 3.1. Risk Preferences.

Functional Preference	Parameter Restrictions
DARA	$\alpha < 1$
CARA	$\alpha = 1$
IARA	$\alpha > 1$
DRRA	$\beta < 0$
IRRA	$\beta > 0$

u denotes utility, \exp denotes exponential, and w is wealth. Parameter restrictions of the utility function are $\theta > 1$, $\alpha \neq 0$, $\beta \neq 0$, and $\alpha\beta > 0$.

Flexibility with the model allows for different preferences as α and β change. Table 3.1 shows the forms of functional preference as parameter restrictions are altered. Using the flexible form of the expo-utility function allows for the evaluation of risk behavior and optimal decision making under different risk preferences.

As discussed earlier, expected utility assumes that evaluating different risky situations allows decision makers to substitute monetary values for the utility of wealth. By valuing the expected utility of a situation with some level of certainty, a decision maker would be able to evaluate the value required for an individual to take on a portfolio of goods that results in an uncertain wealth or, rather, income level. This concept suggests that, in order for an individual to take on a portfolio with greater uncertainty, he/she would need to receive some level of monetary value to be indifferent between the wealth received from the good with certainty and the portfolio containing an additional good that carries uncertainty (Serrao and Coelho, 2000). The additional value needed for a decision maker to be indifferent to the wealth certainty of the initial

investment is also known as the risk premium. The use of a risk premium allows for the evaluation of risk aversion and the decision maker's willingness to pay for risk.

This concept may be applied to the case of grain marketers who are faced with the decision of marketing heterogeneous commodities when one poses increased risks. Valuing the risk premium would indicate what the market may need to compensate marketers if they were to incur additional risks.

Quality, Contracting, and Blending

In marketplace economics, quality plays a determining role in the practices of market players and the price that the markets reflect. Grading quality and finding information create additional costs and risks for the handlers of heterogeneous commodities. Quality variability is a major risk factor that marketers face when trading commodities. The main impacts to quality and quality uniformity lie within the consistency and inadequacy levels. There are three main types of consistency when observing quality: (1) within a package, (2) across packages, and (3) over time (Browbrick, 1992). The impacts of managing the quality consistency have implications for merchandisers and firms. Determining quality or, rather, information seeking adds costs to the process of marketing commodities. Grading has an inherent economic purpose that provides a means of communicating information to the marketplace (Hill, 1990). Definition of grades makes getting information to the marketplace easier and offsets asymmetric information to all parties involved in the commodity trading markets. This grading, in turn, reduces the information costs for traders in the marketplace.

Although grading helps to define quality levels, there are still many costs to ensure quality. There is an inherent tradeoff between costs and quality levels. The costs of quality may arise in three different categories: (1) prevention (contract) costs, (2) appraisal (testing) costs,

and (3) failure (discount and penalty) costs. Prevention costs result because of any action taken to investigate, prevent, or reduce the risk of non-conformity or defects. Appraisal costs are resultant of evaluating the achievement of quality investments and failure costs (Porter and Rayner, 1992). The costs associated with prevention, appraisal, and failure are all incurred so that quality can be controlled. Theoretically, as these costs increase, the quality also increases. Figure 3.1 shows the relationship between these costs and the resulting quality. Viewing costs and quality in the same function implies that there is a point at which optimal quality may exist such that the costs are minimized. There is an underlying assumption that an increased quality-control measure will increase revenues to some degree. In the larger framework of choice and utility, a grain handler would attempt to find this point such that he/she would maximize utility based on the increased portfolio value of incurring risks associated with achieving and maintaining quality.

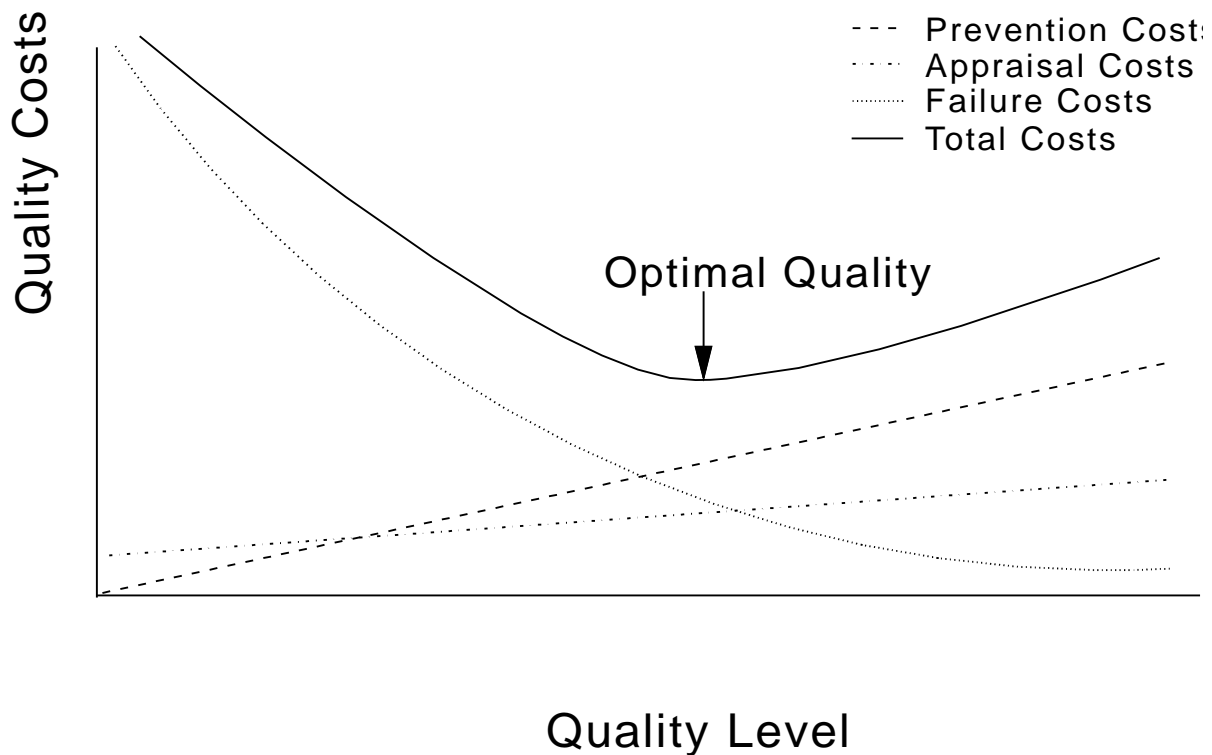


Figure 3.1 Total Quality Management, Optimal Quality with Costs (Porter & Rayner, 1992).

Buyers and merchandizers who face risks as a result of quality uncertainty must develop purchasing strategies to manage risks. Determining optimal strategies to handle quality risks, purchasers often impose contracts and restrictions in order to manage quality uncertainty. When contracted to meet quality specifications, grain merchandizers are exposed to two risk sources: (1) the inability to meet specific requirements and having to sell at a discount, and (2) paying too high of a price for commodities based on false expectations (Wilson and Dahl, 1999). These situations require that merchandisers and farmers be aware of quality standards, mean levels, and the variance of quality so that they can appropriately understand and manage their exposure to risk. When the variance of quality is non-zero and handlers naturally increase risk from a lack of consistency in their assets and uncertainty of not meeting specifications may result in discounts.

Often, buyers attempt to ensure their quality by entering contracts to meet specifications. Contract specifications generally represent the buyers' procurement strategies. Contracts may include a variety of discounts and premiums. The specificity for quality requirements is also included and may go beyond simply meeting a specific level or uniformity. There are spatial and temporal factors that determine quality. Buyers' strategies and subsequent contract specifications often reflect spatial-quality differences because they do not allow purchases from certain geographic locations. In response to these specifications, grain handlers must be able to diversify portfolios in order to hold contracts in alternate-quality differentiated markets (Wilson and Dahl, 1999). Figure 3.2 helps illustrate the impacts for how contracts may be used to develop optimal testing strategies. Point Q^* represents the optimal testing strategy. After this point, the total costs of testing for quality no longer return benefits to increase quality. Contracting limits determine

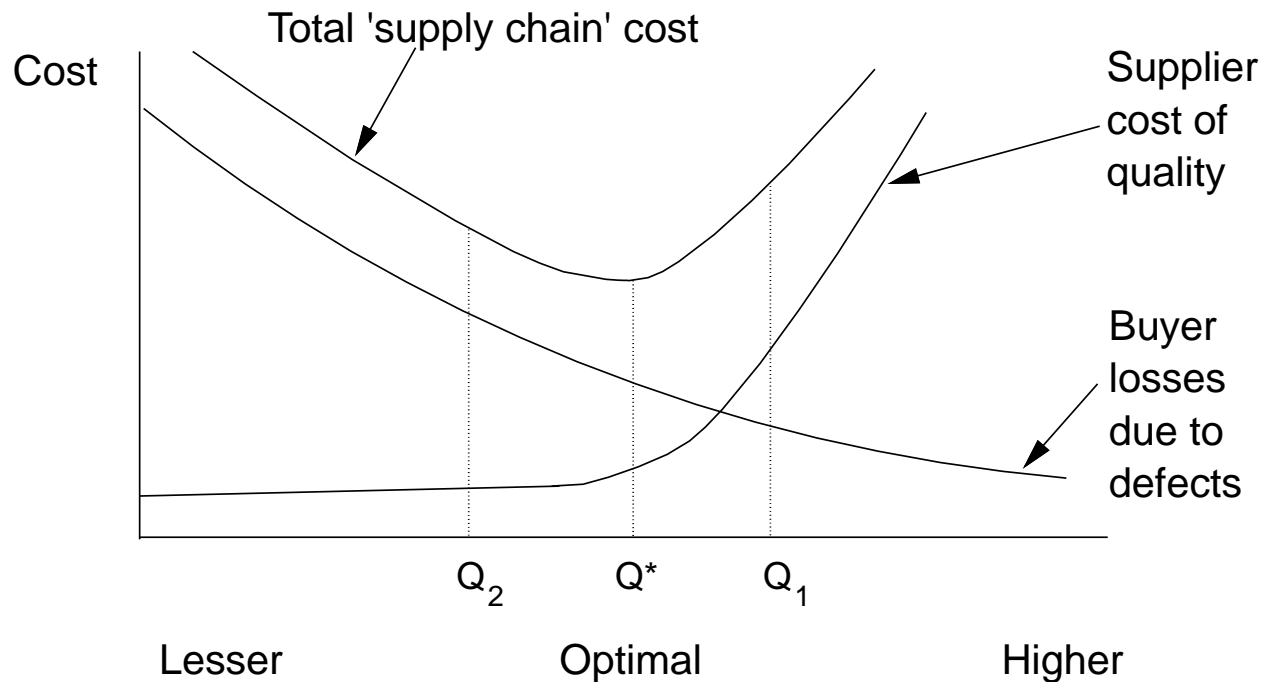


Figure 3.2. Total Quality Management of Buyer and Seller Risk (Porter and Rayner, 1992).

what quality limits the suppliers must meet. If Q_2 represents the quality requirement levels, the buyers' total costs would be higher than the suppliers' cost. Conversely Q_1 would have lower buyer costs while the costs for quality would be greater. When confronted with quality and uncertainty because of quality, buyers may use contracts as a way to mitigate their risks. These contracts may, in turn, affect marketplace values through the discounts and premiums applied, passing risks onto producers and merchandisers. Beyond premiums and discounts, spatial flows may be disrupted due to market signals from the premiums and discounts that arise.

Contract requirements and testing provide a framework to examine the costs of quality for both buyers and sellers. Blending also offers another measure to prevent the loss of quality, however, blending may incur additional costs for the grain handlers due to heterogeneous quality traits. However, there is, generally, a cost associated with blending; that cost may be in the form of additional storage, operating, testing, or premium costs along with additional operational procedures. The purpose of blending is to increase the likelihood that quality specifications are

met, generally, by rearranging a higher-quality lot with a lower-quality lot. When a quality specification is determined, linear programming proves to be a method to choose the optimal blend ratio in order to assure, with some degree of probability, that the quality requirements are met. Imagine the case of two separate lots of soybeans with distinct, differentiated probability distribution functions (pdf). Blending a portion of the higher-quality lot with the lower-quality lot would increase the probability that the newly blended lot would meet the requirements. If additional costs are applied to the higher-quality lots, an optimal choice would blend proportions of each lot such that the requirements are met. Assuming a concave, functional relationship between the costs of blending and quality, there would exist an optimal choice of blending proportions such that the requirements are met.

Summary

The theoretical framework presented in this chapter provides a point foundation to further analyze the impacts that the quality has on commodity markets. The expected utility theory provides an explanation for rational decision making that individuals may choose when faced with uncertainty and risk. A further understanding of risk preference establishes conditions where decision makers may be willing to trade certainty for increased risk. This understanding includes the implications that risk premiums and additional monetary values may provide to individuals who are willing to take on additional uncertainty and risk.

Quality uncertainty provides additional risk factors for both the buyers and sellers. Adopting quality-management techniques helps to alleviate many risks that buyers and sellers face. Contracting allows buyers to establish minimum requirements for the suppliers, and also allows sellers to determine the optimal quality-management procedures to minimize the risks. However, many prevention and quality-management techniques increase the costs in order to

increase quality. Tradeoffs among cost, quality, and the resulting risks create the framework for determining the optimal strategies to select systems to manage all three. Linear programming becomes a valuable tool to determine the optimal strategies to balance the costs and risks while meeting the quality requirements.

CHAPTER 4: EMPIRICAL METHODS

Introduction

There has been a great deal of change in the grain-merchandising industry in the last several years. End users have become more sophisticated in their purchasing and have been analyzing more critical quality components of the grain they are purchasing. Because end users have more knowledge about the quality they require and the variability in quality across origins, users may be willing to apply premiums or discounts to grains that meet or do not meet the requirements. Producers and handlers who are aware of the purchasers' price signals may adjust the marketing schemes to follow the higher price opportunities that exist due to higher-quality preferences.

There are several different aspects that affect quality performance of agriculture commodities. Some quality factors may be due to production practices, variety specification, handling practices, or varying spatial conditions (length of the growing season, soil and nutrient differences, etc.). The focus of this study is the soybeans' protein quality, specifically the amount and concentration of EAA in the proteins. Total protein measurements are thought to be related to the amount of sunlight that a soybean has during its growing season. Regions further from the equator have shorter sunlight during the growing seasons, creating spatial disparities and variability between regions; purchasers may take advantage of these differences to secure proper quality levels.

As mentioned in Chapter 2, many purchasers who are interested in protein quality levels have adjusted their purchasing to ensure adequate protein quality. The buyers have limited purchases only to shipments that have adequate protein levels. Limiting purchase has included rejecting or discounting protein-deficient shipments and not purchasing grain from certain

geographic regions. Furthermore, there are risks that both the buyers and sellers face when specifications are desired. Contracts may be used as a method to determine the appropriate risk sharing between buyers and sellers.

One of this study's goals is to identify EAA in soybeans and to measure the likelihood of meeting end users' specific requirement. As pointed out earlier, EAAs are particularly important to livestock growers because digestibility and the EAAs' nutritional value drive animals' growth (Gast, 2014). The model specified uses the EAA distribution in soybean samples to determine the number of shipments that meet the EAA requirement specifications. From this model, the costs and risks of testing to meet specifications will be determined and interpreted. The following section describes the methods and procedures used to determine the costs and risks of testing for EAAs in a dual-marketing system. A dual-marketing system is one that handles and segregates two differentiated commodities. The dual-marketing chain will contain high-quality (HQ) and low-quality (LQ) soybeans. High-quality soybeans are defined as soybeans that meet quality specifications, and low-quality soybeans do not meet the quality requirements

Testing Model Specifications

The model developed in this study mimics that of a dual-marketing, vertically integrated firm that handles both high-quality and low-quality soybeans. At each point in the supply chain, quality flows are subject to risks from handling and testing. When optimal strategies decide to test at each location, high-quality samples that test bad will be diverted to low-quality flows. Adventitious comingling causes low-quality flows to contaminate high-quality flows at each location and increases the likelihood that the testing samples a bad batch. Adventitious comingling is defined as the unintended or unavoidable mixing of one grain segregation with another one. In this case, adventitious comingling happens when low-quality soybeans are

inadvertently entered into the high-quality segregation flows. Figure 4.1 shows the full supply chain that is modeled.

Furthermore, the model set forth uses stochastic optimization to determine the optimal testing points within the grain-marketing supply chain. More specifically, the model analyzes a dual-marketing system that included segregation of two different states: soybeans that exhibit adequate levels of EAA to meet the requirements and soybeans that do not meet the requirements. The model contains a minimization component that uses a von-Neuman-Morgenstern style utility function. This function allows for decreasing absolute risk and increasing relative risk aversion. The model chooses both the test locations and the intensity of testing, both of which determine the total costs. Testing determines the two different states: (1) high quality, meeting the EAA requirements, and (2) low quality, samples that do not meet the requirements. The final composition of both segregations determines the weighted values of utility for each separated flow. The additional costs of utilizing a system with EAA testing determines the weighted disutility of each segregation. Chapter 3 described the generalized expected utility model. The objective function is specified as follows:

$$MinDU(C) = \sum_{i=1}^2 \delta_i (\lambda - e^{-\phi - c_i^\eta}) \quad (\text{Eq. 4.1})$$

s. a. $X_j \in K_j$,

where

δ is the proportion of flows segregated to each state of quality,

e is the natural logarithm,

λ is a parameter that determines the positiveness of the utility function,

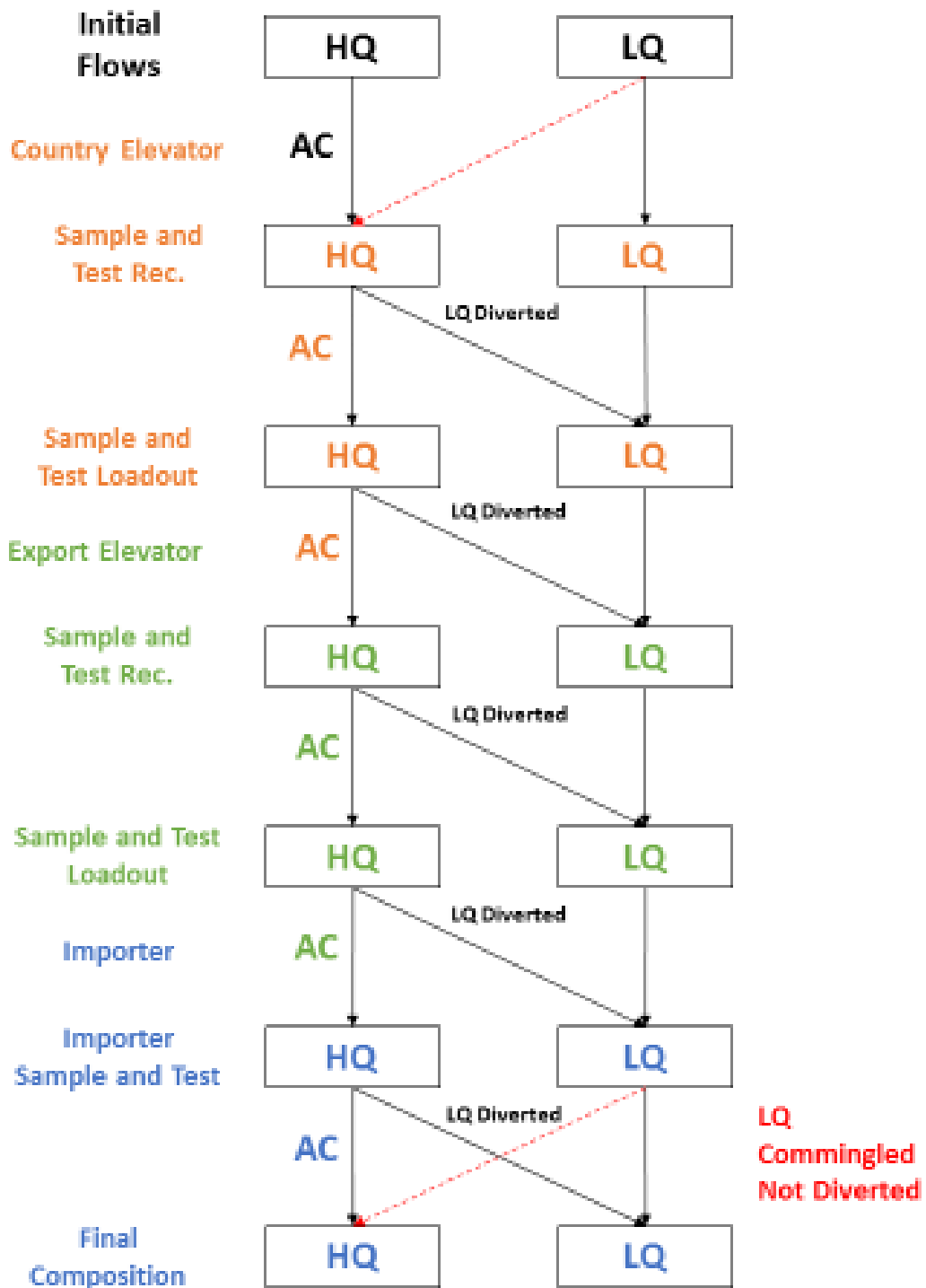


Figure 4.1. Dual-Marketing Testing Model.

ϕ and η are parameters that affect the absolute and relative risk aversion of the utility function, c_i is the additional system costs associated with each quality segregation, X_j is the decision variable vectors of the model ($j = T_k, S_k$), and K_j is the opportunity set of the model.

Specifications of this model determine the optimal testing, location, and intensity by minimizing disutility from the costs incurred by testing for EAA and meeting the requirements. While there is, currently, little information on which to base soybean quality testing, this model has been used to determine optimal testing for other commodities. Previous studies done by Wilson et al. (2006) suggest that this model would have the capacity to understand what risks grain handlers may face if testing were included with soybean grain marketing. Parameters ϕ and η determine the absolute and relative risk aversion; increasing ϕ while holding η constant increases the absolute risk aversion but does not affect the optimal solution. Conversely, increasing η while holding ϕ constant increases the relative risk aversion, and its effect on the objective function is greater than the effect ϕ has on the objective function.

Costs and risks determined by the model may also be used to determine the risk premium. The risk premium compensates the grain handler for potential risks emanating from the detection of lower-quality grain in high-quality flows. The risk premium is derived from the expected value of the system as follows:

$$\pi = EV_{HQ} - CE_{HQ/LQ}, \quad (\text{Eq. 4.2})$$

where

EV_{HQ} is the expected additional cost of a system without testing; the costs are assumed to be zero and

$CE_{HQ/LQ}$ is the certainty equivalent of additional system costs for a dual system.

The premium considers the total costs as well as the risks that grain handlers face from utilizing two different flows, determining the value of being exposed to additional risks and what premium value is required to offset the costs and risks.

Testing Costs

The model presented is set to determine the best testing strategies within a grain-marketing chain based on the risk parameters and additional costs that are required to minimize disutility. Determining best strategies requires an estimation of the additional testing costs. For each state of segregation, there will be separate costs because only soybeans that meet EAA requirements will be tested. For the base case of this study, the costs are defined as follows:

$$C_{HQ} = \sum_{k=1}^n T_k \times TC_k \times S_k \times V_{HQ} + D_{IMP} \times V_{LQ} \quad (\text{Eq. 4.3})$$

$$C_{LQ} = 0, \quad (\text{Eq. 4.4})$$

where

C_{HQ} is the additional costs required to test and segregate higher-quality soybeans that meet EAA requirements;

C_{LQ} is the costs of testing and segregation required for lower-quality soybeans that do not meet EAA requirements. It is assumed that no additional costs are needed to maintain a state of lower quality;

k is the set of locations where testing may be applied: country elevator, receiving and loading; export elevator, receiving and loading; and importer, receiving;

T_k is the binary choice variable reflecting whether tests are applied at location k

TC_k is the individual costs of each test at location k ;

S_k represents the intensity at which tests are conducted at each location, k ;

V_{HQ} is the volume of high-quality soybeans that meet the EAA requirements based on the distribution probability;

D_{IMP} is the discount-applied flows that are diverted from HQ to LQ at the importer; and

V_{LQ} is the volume of low-quality soybeans that do not meet the EAA requirements based on the distribution probability.

The optimization procedure used determines the optimal testing location. The costs from the previous equation are taken at each stage where testing may occur. Costs are then added to the final costs for each state that the model results.

Additional Model Costs

There are three different costs applied at various points in the marketing chain models. Table 4.1 indicates the costs of each case. The cost for testing is applied at each testing location if the optimization model chooses to test. The testing costs are estimated at \$10 for each unit examined. While testing for EAA is not common within grain-marketing chains, the costs are relatively cheap. Near-infrared spectroscopy (NIR) is used to test a small sample of soybeans in order to determine a wide variety of variables, including protein, oil, and all amino acids. Each test responds with all variable outputs and can be done in less than a minute, thus it is practical in its use. Only small samples (less than a bushel) are tested at one time, but due to the short analysis time (1,200/day), it may be practical to use several samples from one shipment without

Table 4.1. Model Costs and Parameters.

Costs	Model Parameters		Source
Testing	\$10/Test	Cost for Testing at a Location	Arthur Killam – UM Research (2015)
Salvage Costs	Uniform Distribution: \$.1-\$1.00/bu	Costs of Discounts and/or Additional Costs to Remarket Soybeans	Wilson et al. (2005)
Nebraska Shipments	Uniform Distribution: \$.05-\$0.10/bu	Higher premium costs paid to purchase and ship soybeans from NE	Industry Contact

increasing costs. Industry has been slow to adopt NIR technology due to low accuracies, but with new advancement and understanding, the technology has become much more accurate. The accuracies range from the upper 80% to lower 90% range (Killam, 2015). NIR testing for EAAs has not become commonplace in the market, thus all costs are an approximation of what the total costs for testing might be. Intensity decision variables determine how many shipments are tested at a specific location. To determine the total costs per bushel, testing costs are only applied to high-quality soybeans remaining at export. Testing costs are not applied to any soybeans diverted into low-quality soybeans.

Salvage costs range from \$.05 to \$.10 with a random, uniform distribution. Salvage costs consist of discounts that may be applied to shipments that do not meet the requirements and/or the additional costs that may arise as a result of remarketing and additional shipping. The costs are estimated based on industry contract terms where discounts are applied starting at \$.10 and going up to \$1.00. Salvage costs are applied to low-quality soybeans diverted from the high-

quality flows at the export elevators. It is assumed that diverting low-quality soybeans has no additional salvage costs within the domestic market because the domestic markets account for accurate pricing without penalties. The final costs are only applied to the final blending model. These costs are applied to shipments from Nebraska that are blended with North Dakota shipments at the export location.

The following cases are analyzed with the model presented. Cases will include testing for one of the five amino acids as well as cases that analyze the probability that all five EAAs meet the requirements. Another case determines the costs and risks based on no testing. The final case includes an additional set of testing locations to determine grain flows for the Nebraska shipments that are blended with North Dakota shipments.

Requirements

Requirements for the model are used to determine what percentage of the flows will meet the quality standards. There are seven different quality standards that may need to be met in any give case of the model. They are: protein, oil, lysine, threonine, tryptophan, and the sum of methionine and cysteine. The protein and oil requirements, taken from industry analysis for what the current market measures and requires, are listed in Table 4.2. EAA requirements were taken from the National Resource Center (NRC) as reported by Merck Veterinary Manuals (2015). Amino-acid requirements for soybeans are not currently measured in the marketplace, and there are no benchmarks to measure what the market may require. These requirements presented in Table 4.2 are utilized for soymeal to feed hogs. The hog market should prove as a valid starting point because it is one of the largest markets for which soybeans are used as meal. The Data section of this chapter discusses the considerations of EAA and the measures in raw soybeans and soybean meal.

Table 4.2. Soybean Quality Requirements.

Protein & Oil Requirements	Preferred	Lower Limit					
Protein	34%	33%					
Oil	18.50%	18%					
Swine EAA Requirements							
Body Weight (kg)	7-5	7-11	11-25	25-50	50-75	75-100	100-135
Lysine	1.7	1.53	1.4	1.12	0.97	0.84	0.71
Methionine	0.49	0.44	0.4	0.32	0.28	0.25	0.21
Threonine	1.05	0.95	0.87	0.72	0.64	0.56	0.49
Tryptophan	0.28	0.25	0.23	0.19	0.17	0.15	0.13
Cysteine	0.47	0.43	0.39	0.33	0.29	0.25	0.22
Methionine + Cysteine	0.96	0.87	0.79	0.65	0.57	0.5	0.43

Data

Data for this study were collected with a sampling study funded by the United States Soybean Export Council and conducted by Dr. Seth Naeve at the University of Minnesota (Naeve, 2013). Samples were taken from 2011-2013 and labeled by zip codes. The study measured the protein, oil, and amino-acid content of all samples taken. This study only focused on a few amino acids termed the Essential Amino Acids (EAA). All Naeve's data points were not used. The focus of the current study was to determine the costs of testing soybean shipments from North Dakota, thus only samples taken from North Dakota were used for all cases that were analyzed. Further data samples from Nebraska were used with the blending model that is presented in the final case.

One important component of the model is determining the minimum requirements that samples needed to meet. The requirements used in this study were gathered from the National Research Center (NRC). Table 4.2 shows the requirements that were gathered from Merck Veterinary Manuals, (2015). Summary statistics for the data collected are referenced in Table 4.3.

The EAA requirements for hogs change depending on the hog's growth stage. These requirements are determined for optimal growth at any given stage. For the purpose of this study, hogs ranging from 75-110 kg were analyzed as the base group. The reasoning was to capture the most likely requirements that purchasers may demand. While lower-weight hogs may require higher EAA, their overall feed intake is much lower than hogs that weigh more. To understand how costs may vary based on requirements, sensitivities were conducted on the requirement levels.

Data were based on amino-acid values in raw soybeans while all requirement levels were based on soybean meal. This data presented an issue with the data and the EAA requirements that came from the NRC. Research conducted by Updaw et al. (1976) determined the protein value of soybean meal based on the oil and protein levels of raw soybeans. This study allowed for protein and oil measures to be transferred into soybean meal after crushing processed the soybeans to soybean meal. Because amino acids are reported as a percentage of protein available, an assumption was made that the amount of EAAs per protein in raw soybeans would be the same as the EAAs per protein in dry soybean meal. The regression equation (Updaw et. al, 1976) used to determine the dry soybean meal was as follows:

$$Z_{ij} = -.1343 + .6712X_i + 1.3203X_j \quad (\text{Eq. 4.5})$$

$$R^2 = .99 \quad ,$$

where

Z_{ij} is the pounds of protein content per pound of soybean meal;

X_i is the oil content of soybeans, expressed as a decimal; and

X_j is the protein content of soybeans, expressed as a decimal.

Protein and oil measurements were taken and used with Equation 4.5 to determine the estimated value of each EAA. Once this step was done, we could compare the values to the nutritional requirements set forth by the NRC data.

Distributions for Randomized Variables

Using data sampled from various geographic locations, the soybeans' quality aspects were analyzed to determine the best-fit distributions for the data gathered. @Risk simulation software was used to determine the best fit. A batch fit command was used to determine the distributions for a set of multivariate data in a single estimation. This procedure created a single distribution equation and formulation for each variable. A correlation matrix was also generated, showing the correlation between each fitted data set. Additional fields in the distribution equation included a RiskCorrmat function that correlated the sampling of the fitted distributions to each correlation variable. Best-fit selection utilized the Akaike Information Criterion (AIC) to determine the best-fit distribution. Tables 4.3 contain the specific variables as well as the graph shape, functional parameters, and correlation matrices.

The "RiskTarget" function uses the distributions to determine the probability that flows will be high quality (HQ) or low quality (LQ) within the two separate states of the model, and the function is represented by P_C and is representative of the cumulative probability of a given target value. P_{HQ} denotes the probability of requirements that will meet specifications based on simulation samples.

$$P_{HQ} = 1 - P_c \quad (\text{Eq. 4.6})$$

The probability for low-quality flows is as follows:

$$P_{LQ} = P_c \quad (\text{Eq. 4.7})$$

This follows through all cases, however, high quality and low quality are determined by different variables and the various requirements that need to be met. Several cases may use more than one variable to determine if high-quality standards are met. The joint probability of meeting these requirements determines the percentage of flow. Joint probability is a discrete method to determine the likelihood of meeting multiple requirements and is represented as follows:

$$P_{HQ}(1,0) = \frac{\sum_{i=0}^k P_k(X_1 \leq x_1, X_2 \leq x_2, \dots, X_n \geq x_n)}{k}, \quad (\text{Eq. 4.8})$$

where

P_{HQ} is the joint probability that any given sample will meet the requirements for all variables over k simulations,

k is the number of the random simulations drawn,

P_k is the discrete joint probability outcome (0,1) that all variables meet the requirements for random draw k ,

X_n is the requirement level for variable n , and

x_n is the random sample that is drawn based on distribution parameters for variable n .

Table 4.3. Soybean-Sampling Data Summary.

Table 4.3	Protein	Oil 13%	Total EAA	CAAV	Lysine	Threonine	Tryptophan	Methionine	Cysteine
North Dakota									
Mean	34.01%	18.20%	5.64	16.62%	2.56	1.53	0.46	0.55	0.54
Standard Deviation	1.97%	1.41%	0.22	0.79%	0.15	0.08	0.04	0.02	0.04
Minimum	29.51%	14.30%	5.08	14.48%	2.17	1.35	0.37	0.49	0.38
Maximum	40.29%	21.31%	6.17	19.20%	2.86	1.77	0.56	0.61	0.64
Nebraska									
Mean	34.60%	18.32%	5.71	16.52%	2.59	1.54	0.47	0.56	0.55
Standard Deviation	1.52%	1.39%	0.19	0.67%	0.13	0.08	0.03	0.03	0.04
Minimum	28.68%	13.42%	5.08	14.61%	2.24	1.35	0.39	0.49	0.39
Maximum	40.27%	21.62%	6.28	19.93%	2.91	1.77	0.57	0.63	0.65
All States									
Mean	34.63%	18.51%	5.71	16.50%	2.58	1.55	0.47	0.56	0.54
Standard Deviation	1.74%	1.38%	0.19	0.66%	0.14	0.09	0.04	0.03	0.04
Minimum	28.59%	11.26%	4.97	13.50%	2.08	1.32	0.30	0.46	0.36
Maximum	42.62%	24.02%	6.50	19.93%	3.01	1.92	0.61	0.80	0.87

Models utilizing joint probability to determine the likelihood of high quality also determined the probability of low quality, P_{LQ} , using the following equation:

$$P_{LQ} = 1 - P_{HQ} \quad (\text{Eq. 4.9})$$

Quality Distributions

Table 4.4 shows the results of the batch fit and the distributions of samples taken from North Dakota soybeans. There were 201 samples used to determine the best fit. The correlation matrix at the end aided in the random samples that were taken from the simulation procedure. Throughout the simulation, high-quality lots were analyzed to determine if the requirement levels were met at any given point in the marketing model. Samples that met all the requirements were used to determine the best-fit distributions for high-quality flows within the marketing model. Table 4.5 shows the best-fit distribution parameters of EAAs that met the high-quality specifications based on EAA requirements.

Blending Model Description

The first model uses a single origin to supply exports, as shown in Figure 4.1. A second model that optimizes the testing strategies for two locations with an additional blending component is presented. Figure 4.2 shows the additional supply chain testing locations along with the blending component. The purpose of this model is to determine the best strategies that may be used not only to test, but also to blend soybeans from different origins that have higher quality specifications. In this case, Nebraska is the alternative origin.

Table 4.4. ND Quality Best Fit Distributions.

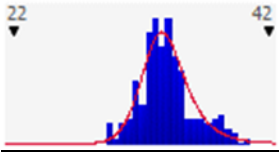
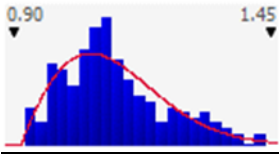
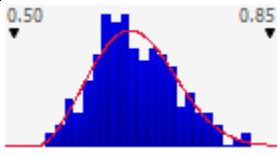
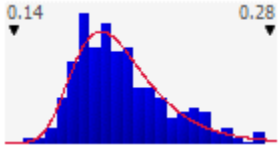
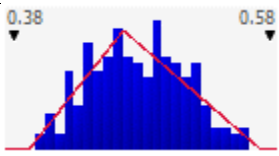
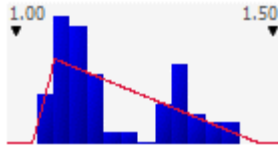
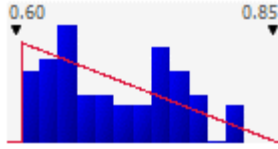
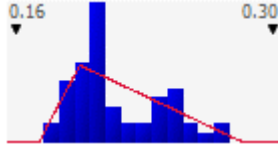
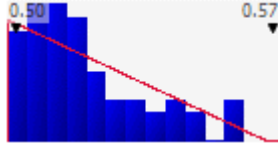
<u>ND Quality Best-Fit Distributions</u>					
Variable	Graph		Distribution Parameters		
Protein			<u>RiskLogLogistic(23.9053,9.9110,9.3228)</u>		
Lysine			<u>RiskWeibull(1.8620,0.21077,RiskShift(0.93259))</u>		
Threonine			<u>RiskWeibull(2.6381,0.14304,RiskShift(0.54149))</u>		
Tryptophan			<u>RiskExtValue(0.189258,0.018605)</u>		
Methionine + Cysteine			<u>RiskTriang(0.39717,0.46705,0.56819)</u>		
<u>Correlation Matrix</u>	Protein	Lysine	Threonine	Tryptophan	Methionine + Cysteine
Protein	1	.820	.742	.744	.675
Lysine	.820	1	.586	.835	.523
Threonine	.742	.586	1	.650	.452
Tryptophan	.744	.835	.650	1	.536
Methionine + Cysteine	.675	.523	.452	.536	1

Table 4.5. North Dakota's High-Quality Soybean Distributions.

ND High-Quality EAA Best-Fit Distributions				
<u>Variable</u>	<u>Graph</u>		<u>Distribution Parameters</u>	
Lysine			RiskTriang(1.04507,1.08650,1.46248)	
Threonine			RiskTriang(0.61264,0.61264,0.84772)	
Tryptophan			RiskTriang(0.17602,0.19723,0.28105)	
Methionine + Cysteine			RiskTriang(0.500143,0.500143,0.566823)	
<u>Correlation Matrix</u>	Lysine	Threonine	Tryptophan	Methionine + Cysteine
Lysine	1	.741	.832	.376
Threonine	.741	1	.7166	.230
Tryptophan	.832	.716	1	.297
Methionine + Cysteine	.376	.203	.297	1

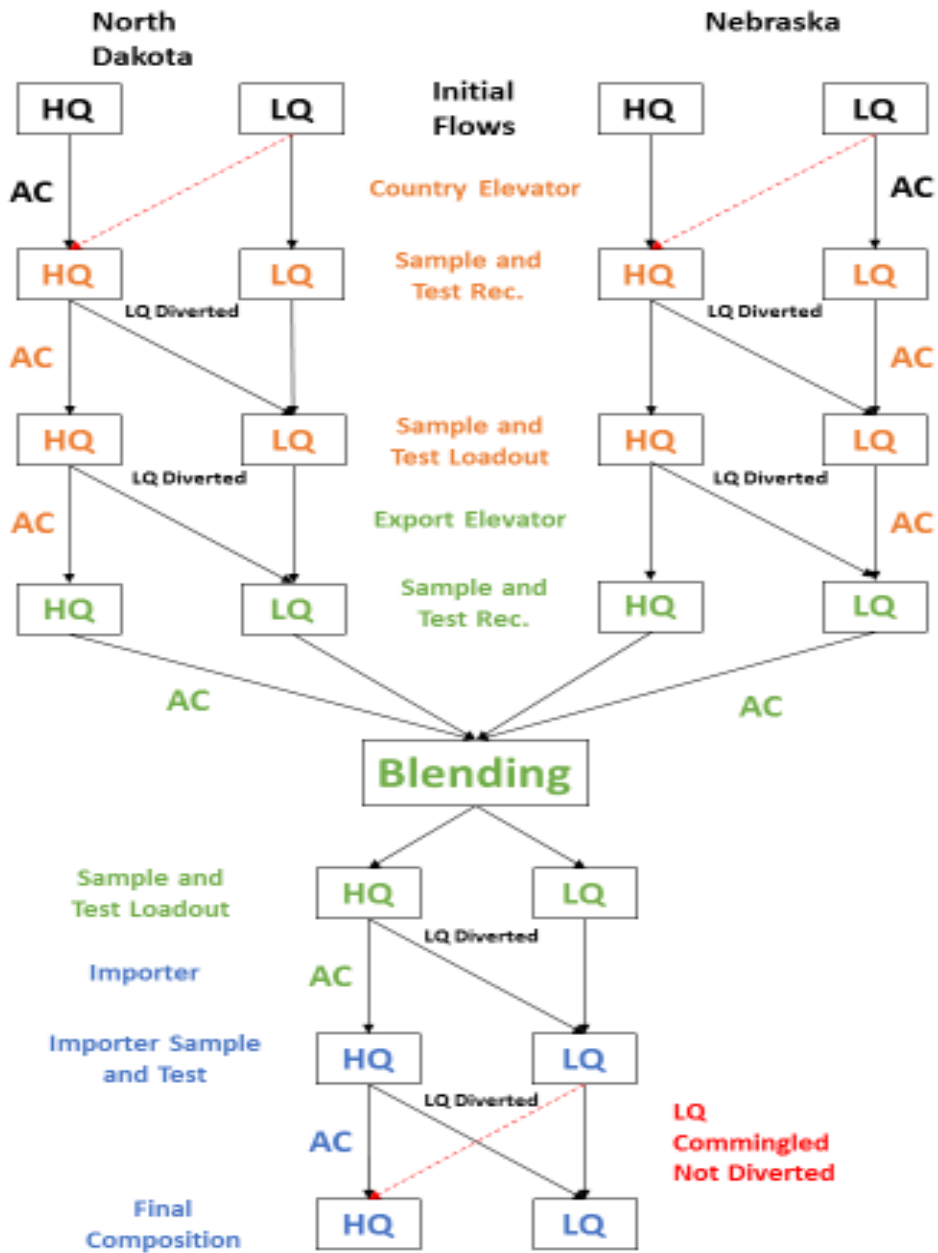


Figure 4.2. Dual-Marketing Testing Model with Blending Component.

Further mathematical representations are needed to incorporate the blending component with the optimization model. The purpose of blending is to supplement the lower-quality soybeans from North Dakota with soybeans of higher quality, in this case originating from Nebraska. Additional constraints are added to the optimization model in order to ensure that the blending requirements are met. The mathematical specifications of the blending model are as follows:

$$Min(C) = \sum_{i=1}^2 \delta_i (\lambda - e^{-\phi c_i^\eta}) \quad (\text{Eq. 4.12})$$

s. a. $X_j \in K_j$

s. t.

$$0 \leq B_{ND} \leq 1$$

$$B_{NE} = 1 - B_{ND} \geq 0$$

$$Q_s \geq R_s, \quad p = .95,$$

where

δ is the proportion of flows segregated to each state of quality,

e is the natural logarithm,

λ is a parameter that determines the positiveness of the utility function,

ϕ and η are parameters that affect the absolute and relative risk aversion of the utility function,

c_i is the additional system costs associated with each quality segregation,

B_{ND} is the percentage of North Dakota HQ soybeans blended with Nebraska HQ soybeans,

B_{NE} is the percentage of Nebraska HQ soybeans blended with North Dakota HQ soybeans,

Q_s is the random quality variable for variable s ,

R_s is the minimum requirement for variable s ,

X_j is the decision variable vectors of the model ($j = T_{k,l}, S_{k,l}, B_l$), and

K_j is the model's opportunity set. Several additional decision variables are added to this model. The first set of decision variables is the additional testing locations for soybeans shipped from Nebraska. These locations also includes testing the intensity decision variables for each location. All parameters for these additional testing locations and intensities are constrained by discrete parameters of 0 and 1 for the testing decision. Testing the intensity decision variables is also discrete, ranging from 1:5-5:5; 1:5 would be to test 1 of every 5 shipments and to reject all if bad or accept all if good. There is also a blending decision variable that determines the percentage of flows from each destination, and it is a continuous decision variable from 0-1. Additionally, there are new costs for the new set of decision variables. The costs of the blending model is as follows:

$$C_{HQ} = \sum_{l=1}^m \sum_{k=1}^n \{B_l \times (T_{k,l} \times TC_{k,l} \times S_{k,l} \times V_{HQ} + D_{IMP} \times V_{LQ})\} + \sum B_2 \times P_{NE} \times V_{HQ} \quad (\text{Eq. 4.13})$$

$$C_{LQ} = 0, \quad (\text{Eq. 4.14})$$

where

C_{HQ} is the additional cost required to test, segregate, and blend the higher-quality soybeans that meet the EAA requirements;

C_{LQ} is the cost of testing and segregation that are required for lower-quality soybeans that do not meet the EAA requirements. It is assumed that no additional costs are needed to maintain a state of lower quality;

k is the set of locations where testing may be applied: country elevator, receiving and loading; export elevator, receiving and loading; and importer, receiving;

l is the portion of the marketing chain that represents each sub-chain of the blending model: North Dakota or Nebraska;

$T_{k,l}$ is the binary choice variable reflecting whether the tests are applied at location k in sub-chain l ;

B_l is the decision variable that determines how much to blend from each sub-chain, l ;

$TC_{k,l}$ is the individual costs for each test at location k in sub-chain l ;

$S_{k,l}$ represents the intensity at which tests are conducted at each location, k , in sub-chain l ;

P_{NE} is the premium added to shipments from Nebraska;

V_{HQ} is the volume of high-quality soybeans that meet the EAA requirements based on the distribution probability in each sub-chain;

D_{IMP} is the discount-applied flows that are diverted from HQ to LQ at the importer; and

V_{LQ} is the volume of low-quality soybeans diverted from HQ to LQ at the importer.

As in earlier models, @Risk used batch-fit data samples to determine the best-fit distribution tables for North Dakota and Nebraska. North Dakota's best-fit distributions were listed previously. Table 4.6 shows the best-fit distribution parameters for samples taken from Nebraska soybeans and determines the likelihood (P_{HQ} & P_{LQ}) that will represent the two different states of quality. Nebraska samples were also sorted by observations that met all EAA quality requirements. The best-fit distribution of high-quality Nebraska beans are listed in Table 4.7 along with the correlation matrix that was determined with the best-fit distribution.

Table 4.6. Nebraska's Quality Distributions.

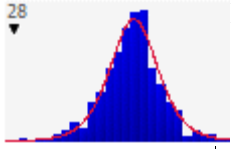
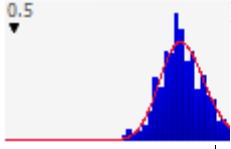
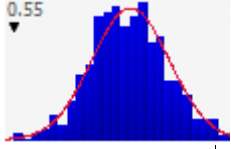
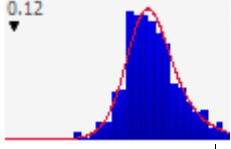
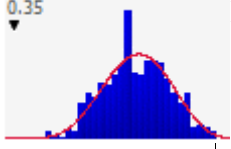
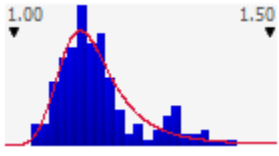
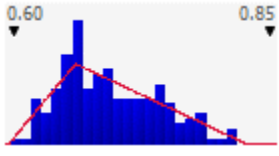
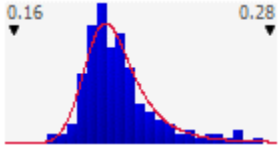
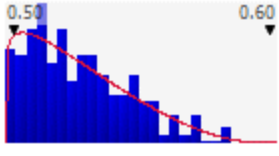
Nebraska's Quality Best-Fit Distributions					
Variable	Graph		Distribution Parameters		
Protein			RiskLogistic(34.58543,0.82291)		
Lysine			RiskGamma(59.106,0.010695,RiskShift(0.521045))		
Threonine			RiskNormal(0.687429,0.042690)		
Tryptophan			RiskLogLogistic(0.131394,0.074316,8.1067)		
Methionine + Cysteine			RiskBetaGeneral(5.8630,5.1957,0.36595,0.60922)		
<u>Correlation Matrix</u>					
Correlation	Protein	Lysine	Threonine	Tryptophan	Methionine + Cysteine
Protein	1	.747	.928	.618	.557
Lysine	.747	1	.423	.797	.342
Threonine	.628	.423	1	.504	.279
Tryptophan	.618	.797	.504	1	.256
Methionine + Cysteine	.557	.342	.279	.256	1

Table 4.7 Nebraska's High-Quality Soybeans Distributions.

Nebraska's High-Quality EAA Best-Fit Distribution				
Variable	Graph	Distribution Parameters		
Lysine		RiskLogLogistic(1.01975,0.13688,3.7064)		
Threonine		RiskTriang(0.60268,0.66445,0.82261)		
Tryptophan		RiskLogLogistic(0.170433,0.036947,4.8048)		
Methionine + Cysteine		RiskBetaGeneral(1.1151,2.7037,0.500204,0.591413)		
<u>Correlation Matrix</u>				
Correlation	Lysine	Threonine	Tryptophan	Methionine + Cysteine
Lysine	1	.453	.708	.412
Threonine	.453	1	.549	.076
Tryptophan	.708	.549	1	.299
Methionine + Cysteine	.412	.076	.299	1

Specified Model Cases

The disutility optimization model uses the additional costs as well as the portfolio of HQ and LQ flows to determine the optimal testing locations and intensities. However, there are varying circumstances for different variables and marketing strategies. For the purpose of understanding the grain marketers' different preferences and the various effects on costs, several cases were set forth using the dual-marketing system. Structurally, the first five cases were the same, with differing applications of testing, flows, costs, and requirements. The sixth case introduced a blending option. This case included an additional marketing chain to test and blend soybeans shipped from Nebraska. The following cases offer descriptions and extensive charts to show the differing aspects of the separate cases as well as how the outputs are reported. Table 4.8 provides a synopsis for what each case is testing.

Table 4.8. Case Summarization.

	Soybean Origins	Testing Protein	EAA Tests	Testing Oil	Sensitivities
Case 1	ND	No	No	No	Requirements
Case 2	ND	Yes	No	No	Requirements, Testing Costs, Accuracies, Salvage Costs
Case 3	ND	Yes	No	Yes	Requirements, Testing Costs, Accuracies, Salvage Costs
Case 4	ND	No	Yes: One	No	Testing Costs, Accuracies, Salvage Costs
Case 5	ND	No	Yes: All	No	Requirements, Testing Costs, Accuracies, Salvage Costs
Case 6	ND/NE	No	Yes: All	No	Requirements, Testing Costs, Accuracies, Salvage Costs

Case 1: No Testing

The first case is used to determine the risks of conforming to a buyer's protein requirements based on a 34% protein level. Figure 4.3 shows the various stages of the marketing chain where testing will be applied, the comingling risks, and the accountability of comingling exposure for the grain handler at that stage. The model is intended to simulate a normal marketing chain that recognizes protein quality differences and is influenced to prioritize shipments that will meet the 34% protein requirements. Although the model is designed with no testing, they were applied at the importer's receiving level in order to initiate constraints for the minimization procedure and to evaluate the content of the final shipment that is exported. Outputs for risks, costs, and the composition of high and low qualities are relevant for analysis. These outputs includes the average for the simulated iterations as well as the standard deviations. These results provide a benchmark for the following models and the various qualities that are analyzed. Adventitious comingling and handler accountability are applied at all locations per Figure 4.1. Random samples drawn from all simulations determine the amount of the supply that is diverted or not, based on a triangular distribution defined as (.001, .01, .025) and (.8, .95, 1), respectively.

Sensitivities are conducted on several select variables that are crucial to testing in the marketing chain. For this case, the protein requirement is adjusted to 33% in order to determine the impacts of the requirement levels. The industry standards are set at 34% with the allowable tolerance down to 33%. Discounts are applied to qualities between 33% and 34% (correspondence with industry traders). Protein values that measure below 33% are rejected and must be diverted to other buyers, thus creating salvage costs, such as being soybeans repurposed to other buyers. Salvage costs are based on a uniform distribution (.1, 1). Generally, discounts for

Case 1- No-Testing			
Initial Flows of Quality			
Protein			
	0.34		
Distribution of Flows - 2 Segregations			
High Quality (HQ)	Low Quality (LQ)		
Marketing Chain	Allow for Testing	Adventitious Commingling	Accountability
On-Farm	No	None	Yes
Country Elevator			
Receiving	No	Elevator Comingling	Yes
Loading	No	Shipping Comingling	
Export Elevator			
Receiving	No	Elvator Comingling	Yes
Loading	No	Shipping Comingling	
Importer			
Receiving	Yes	None	None
Testing & Model Risk Parameters			
	Commingling Rates	Accountability	Sampling Distribution
On-Farm	Triangular Dist (.001, .01, .025)	Triangular Dist (.8, .95, 1)	Hypergeometric Dist
Country Elevator	Triangular Dist (.001, .01, .025)	Triangular Dist (.8, .95, 1)	Hypergeometric Dist
Export Elevator	Triangular Dist (.001, .01, .025)	Triangular Dist (.8, .95, 1)	Hypergeometric Dist
Importer	Triangular Dist (.001, .01, .025)	Triangular Dist (.8, .95, 1)	Hypergeometric Dist
Salvage Costs	Distribution		
Importer Receiving	Risk Uniform(.1,1)		
Testing	Accuracy	Cost	
NIR	92%	\$10	
Relevant Outputs			
Simulation Procedure	1000 Iteration Simulation - No Optimal Search		
	Testing Location		Testing Intensity
Decision Variables	Yes/No - 1/0		Test Every:Out of N
Importer: Receiving*	Yes - 1		1:1
Output Variables	Minimum	Mean	St. Dev
*Importer Receiving will be not be used as a decision variable. It is assumed that importers will always test at a 1:1 rate.			

Figure 4.3. Model Specifications for Case 1.

Case 2 - Testing Protein			
Initial Flows of Quality			
Probability of Protein Meet Requirements			
Protein			
	34%		
Distribution of Flows - 2 Segregations			
High Quality (HQ)	Low Quality (LQ)		
Marketing Chain	Allow for Testing	Adventitious Commingling	Accountability
On-Farm	No	None	Yes
Country Elevator			
Receiving	Yes	Elevator Comingling	Yes
Loading	Yes	Shipping Comingling	
Export Elevator			
Receiving	Yes	Elvator Comingling	Yes
Loading	Yes	Shipping Comingling	
Importer			
Receiving	Yes	None	None
Testing & Model Risk Parameters			
	Commingling Rates	Accountability	Sampling Distirbution
On-Farm	Triangular Dist (.001, .01, .025)	Triangular Dist (.8, .95, 1)	Hypergeometric Dist
Country Elevator	Triangular Dist (.001, .01, .025)	Triangular Dist (.8, .95, 1)	Hypergeometric Dist
Export Elevator	Triangular Dist (.001, .01, .025)	Triangular Dist (.8, .95, 1)	Hypergeometric Dist
Importer	Triangular Dist (.001, .01, .025)	Triangular Dist (.8, .95, 1)	Hypergeometric Dist
Salvage Costs	Distribution		
Importer Receiving	Risk Uniform(.1,1)		
Testing	Accuracy	Cost	
NIR	92%	\$10	
Relevant Outputs			
Simulation Procedure	Risk Optimizer - 1000 Iterations, 1000 Simulations		
	Testing Location		Testing Intensity
Decision Variables	Yes/No - 1/0		Test Every:Out of N
On-Farm	No - 0		N/A
Country Elevator: Receiving	Yes/No - 1/0		1:5 -5:5
Country Elevator: Loading	Yes/No - 1/0		1:5 -5:5
Export Elevator: Receiving	Yes/No - 1/0		1:5 -5:5
Export Elevator: Loading	Yes/No - 1/0		1:5 -5:5
Importer: Receiving*	Yes - 1		1:1
Output Variables	Minimum	Mean	
Expected Utility	Yes	Yes (1000 Sim)	
Additional Export Costs		Yes (1000 Sim)	
Buyer Risk		Yes (1000 Sim)	
Seller Risk		Yes (1000 Sim)	
HQ Segregated Flows		Yes (1000 Sim)	
Risk Premium		Yes (1000 Sim)	
Probability of EAA Meeting Requirements			
*Importer Receiving will be not be used as a decision variable. It is assumed that importers will always test at a 1:1 rate.			

Figure 4.4. Model Specifications for Case 2.

protein are based on a 1:1 ratio. This discount schedule means that \$.10 is discounted for each .1% protein point below 34% down to 33%.

Case 2: Protein Testing

The second case uses stochastic optimization to determine the optimal testing locations and intensity to minimize disutility. Similarly to the first case, a marketing chain is used to simulate the comingling of high-quality and low-quality soybeans. Figure 4.4 shows the marketing chain, comingling risks, handling accountability, costs, risk parameters, and outputs that define the model. As with the first model, the protein requirements are set at 34%. Initial segregated flows are determined by distributions taken from soybean samples. High-quality soybeans represent the likelihood that flows will meet the 34% protein requirements. The risk parameters are the same for case 2 as they were in case 1. The objective function aims to minimize the disutility of additional costs each state. There are no additional costs for the low-quality state, and all costs are additional to the high-quality flows. The ending-quality probabilities are the main components, along with costs and risk parameters, of the optimized disutility function.

The decision variables are the testing locations and the intensities at which to test. The testing locations are Yes = 1 and No = 0. The intensities are determined by a value ranging from 1-5. A testing intensity of 1 indicates examining 1 of every 5 transport units while a 5 would indicate testing 5 of 5 shipments. Importer testing assumes it is done on every shipment received. The testing costs are determined at each stage of the marketing chain; these costs include testing and salvage costs. Because costs change for each simulation, averages are reported over simulations. Additional probability tests are used to determine the likelihood that, based on the protein tested, the EAA requirements would be met. Distributions of all EAA samples are taken

from samples that meet protein requirements. Probabilities of the EAAs meeting the requirements are determined jointly. Determining if EAAs meet the requirements after testing for protein explains how accurately the protein values will preserve EAA quality through the marketing chain. In the second case, several sensitivities are conducted to analyze the effects of changing different costs and risk variables. The first sensitivity is used to analyze the effects of alternate protein requirements at 33%. Initial flows should be adjusted for the likelihood of meeting the new requirements. Testing costs are changed from \$10 to \$20, and testing is analyzed when accuracies are adjusted from 92% to 87.5%. The final sensitivity determines the effects of increased salvage costs from a uniform distribution, (\$1, \$1) to (\$.75, \$1.5).

Case 3: Testing for Protein and Oil

The third model determines the cost and testing procedure to meet the requirements for both protein and oil. This is shown in figure 4.5. These two quality measures are the two benchmarks which the market tests to determine quality. Case 3 uses sampling data to determine the likelihood that both the protein and oil requirements are met. High- and low-quality flows are determined if the probabilities of meeting the requirements for both protein and oil are jointly met. The base requirements for high and low quality are set at 33% and 18.5% for oil. All mechanisms are similar through the marketing chain as they were in case 2. However, there is no determination about if the EAAs meet requirements because oil is not perceived to be a determinant of the soybeans' EAA composition. Sensitivities are run as they were for case 2. Testing and accuracy cost sensitivities will be the same. Sensitivities for the requirements are adjusted to 34% for protein and 18.5% for oil. Figure 4.5 shows the specifications for this case.

Case 4: Testing for a Single Amino Acid

Case 4, as illustrated in figure 4.6, is an evaluation for testing a single amino acid through the marketing chain. The optimization procedure is used to determine the optimal testing strategy, location, and intensity in order to minimize disutility from costs. Optimization is based on testing to meet the EAA components, i.e., lysine, requirements. Flows are determined from the likelihood that lysine distributions meet the requirements of .84. The marketing chain is the same as it is for case 3, including the testing and cost parameters. Sensitivities are also similar to case 3, however, no sensitivities are conducted in regards to the lysine requirements. The testing costs are adjusted to \$20; the testing accuracies are changed to 87.5%; and salvage costs range from \$.75-\$1.5.

Case 5: Testing EAA

The fifth case optimizes the strategies to test soybeans for all amino acids, as shown in figure 4.7. The distribution of four different quality requirements is used to determine if the sampled lots meet the requirements. Lysine, threonine, and tryptophan need to meet the requirements of .84, .56, and .15, respectively. The sum of methionine and cysteine has to meet a requirement of .5. The reasoning is that cysteine may be used supplement methionine if there is not enough methionine to meet the requirements. The joint probability of meeting these four requirements determines the flows of high and low quality in the model. Again, marketing-chain parameters are the same as they were for the previous case. Sensitivities are conducted on EAA requirement to determine the effects when they are lowered. Model specifications list the requirements' adjustments. Further sensitivities are the same as the previous case, and the testing costs, testing accuracies, and salvage costs are adjusted.

Case 6: Blending Model

The final blending-model case determines the impacts of blending shipments from North Dakota with shipments from Nebraska. Previous models have analyzed a single, dual-marketing chain while this case uses the flows from two different origins to measure comingling and handler accountability. Figure 4.8 shows the specifications for the blending model. Similar to the other cases, accountability, comingling, and testing are applied at various stages in the marketing chain. Two separate marketing chains are used, one for North Dakota and one for Nebraska. The flows are the same as the other cases until the export receiving level. At this point, blending is added. An additional decision variable is utilized with the optimization to determine the optimal amount of ND and NE soybeans to blend. Costs are added to any beans shipped from Nebraska. It is assumed that shipments from Nebraska have a weaker basis than North Dakota beans do and that additional costs are added to Nebraska shipments. A uniformed distribution uses random draws to determine the additional costs between \$.05 and \$.10. More constraints are also added to the optimization. When the two different chains are blended, it is important that the flow combination meets the specified EAA requirements. Random draws from quality distributions of either state are used to determine if the EAA specifications are met. The optimization requires that these specifications be met. However, not all iterations of a simulation result in this requirement being met; a soft constraint is added. If the requirements are not met, penalties are applied to the simulation. A second constraint is added to ensure that the total amount blended together is enough to fill a cargo hold (330,000 bu.). This constraint is intended to simulate export strategies for purchasing and blending. Once the two different origins are blended, the remainder of the marketing chain is similar to the other cases.

Case 3 - Testing Protein and Oil Joint Dist			
Initial Flows of Quality			
Joint Distribution Probability of Meeting Protein and Oil			
Protein	Oil		
33%	18%		
Distribution of Flows - 2 Segregations			
High Quality (HQ)	Low Quality (LQ)		
Marketing Chain	Allow for Testing	Adventitious Commingling	Accountability
On-Farm	No	None	Yes
Country Elevator			
Receiving	Yes	Elevator Commingling	Yes
Loading	Yes	Shipping Commingling	
Export Elevator			
Receiving	Yes	Elevator Commingling	Yes
Loading	Yes	Shipping Commingling	
Importer			
Receiving	Yes	None	None
Testing & Model Risk Parameters			
	Commingling Rates	Accountability	Sampling Distribution
On-Farm	Triangular Dist (.001, .01, .025)	Triangular Dist (.8, .95, 1)	Hypergeometric Dist
Country Elevator	Triangular Dist (.001, .01, .025)	Triangular Dist (.8, .95, 1)	Hypergeometric Dist
Export Elevator	Triangular Dist (.001, .01, .025)	Triangular Dist (.8, .95, 1)	Hypergeometric Dist
Importer	Triangular Dist (.001, .01, .025)	Triangular Dist (.8, .95, 1)	Hypergeometric Dist
Salvage Costs	Distribution		
Importer Receiving	Risk Uniform(.1,1)		
Testing	Accuracy	Cost	
NIR	92%	\$10	
Relevant Outputs			
Simulation Procedure	Risk Optimizer - 1000 Iterations, 1000 Simulations		
	Testing Location		Testing Intensity
Decision Variables	Yes/No - 1/0		Test Every:Out of N
On-Farm	No - 0		N/A
Country Elevator: Receiving	Yes/No - 1/0		1:5 -5:5
Country Elevator: Loading	Yes/No - 1/0		1:5 -5:5
Export Elevator: Receiving	Yes/No - 1/0		1:5 -5:5
Export Elevator: Loading	Yes/No - 1/0		1:5 -5:5
Importer: Receiving*	Yes - 1		1:1
Output Variables	Minimum	Mean	
Expected Utility	Yes	Yes (1000 Sim)	
Additional Export Costs		Yes (1000 Sim)	
Buyer Risk		Yes (1000 Sim)	
Seller Risk		Yes (1000 Sim)	
HQ Segregated Flows		Yes (1000 Sim)	
Risk Premium		Yes (1000 Sim)	

Figure 4.5. Model Specifications for Case 3.

Case 4 - Testing for One EAA - Lysine			
Initial Flows of Quality			
Probability of Meeting Lysine Requirements			
Lysine			
	0.84		
Distribution of Flows - 2 Segregations			
High Quality (HQ)	Low Quality (LQ)		
Marketing Chain			
	Allow for Testing	Adventitious Commingling	Accountability
On-Farm	No	None	Yes
Country Elevator			
Receiving	Yes	Elevator Comingling	Yes
Loading	Yes	Shipping Comingling	
Export Elevator			
Receiving	Yes	Elevator Comingling	Yes
Loading	Yes	Shipping Comingling	
Importer			
Receiving	Yes	None	None
Testing & Model Risk Parameters			
	Commingling Rates	Accountability	Sampling Distribution
On-Farm	Triangular Dist (.001, .01, .025)	Triangular Dist (.8, .95, 1)	Hypergeometric Dist
Country Elevator	Triangular Dist (.001, .01, .025)	Triangular Dist (.8, .95, 1)	Hypergeometric Dist
Export Elevator	Triangular Dist (.001, .01, .025)	Triangular Dist (.8, .95, 1)	Hypergeometric Dist
Importer	Triangular Dist (.001, .01, .025)	Triangular Dist (.8, .95, 1)	Hypergeometric Dist
Salvage Costs	Distribution		
Importer Receiving	Risk Uniform(.1,1)		
Testing	Accuracy	Cost	
NIR	92%	\$10	
Relevant Outputs			
Simulation Procedure	Risk Optimizer - 1000 Iterations, 1000 Simulations		
	Testing Location		Testing Intensity
Decision Variables	Yes/No - 1/0		Test Every:Out of N
On-Farm	No - 0		N/A
Country Elevator: Receiving	Yes/No - 1/0		1:5 -5:5
Country Elevator: Loading	Yes/No - 1/0		1:5 -5:5
Export Elevator: Receiving	Yes/No - 1/0		1:5 -5:5
Export Elevator: Loading	Yes/No - 1/0		1:5 -5:5
Importer: Receiving*	Yes - 1		1:1
Output Variables	Minimum	Mean	
Expected Utility	Yes	Yes (1000 Sim)	
Additional Export Costs		Yes (1000 Sim)	
Buyer Risk		Yes (1000 Sim)	
Seller Risk		Yes (1000 Sim)	
HQ Segregated Flows		Yes (1000 Sim)	
Risk Premium		Yes (1000 Sim)	
*Importer Receiving will be not be used as a decision variable. It is assumed that importers will always test at a 1:1 rate.			

Figure 4.6. Model Specifications for Case 4.

Case 5 - Testing EAA Meets 4 EAA requirements			
Initial Flows of Quality			
Joint Distribution of Meeting 4 EAA requirements			
Lysine	Treonine	Tryptophan	Methionine + Cystine
0.84	0.56	0.15	0.5
Distribution of Flows - 2 Segregations			
High Quality (HQ)	Low Quality (LQ)		
Marketing Chain	Allow for Testing	Adventitious Commingling	Accountability
On-Farm	No	None	Yes
Country Elevator			
Receiving	Yes	Elevator Comingling	Yes
Loading	Yes	Shipping Comingling	
Export Elevator			
Receiving	Yes	Elvator Comingling	Yes
Loading	Yes	Shipping Comingling	
Importer			
Receiving	Yes	None	None
Testing & Model Risk Parameters			
	Commingling Rates	Accountability	Sampling Distribution
On-Farm	Triangular Dist (.001, .01, .025)	Triangular Dist (.8, .95, 1)	Hypergeometric Dist
Country Elevator	Triangular Dist (.001, .01, .025)	Triangular Dist (.8, .95, 1)	Hypergeometric Dist
Export Elevator	Triangular Dist (.001, .01, .025)	Triangular Dist (.8, .95, 1)	Hypergeometric Dist
Importer	Triangular Dist (.001, .01, .025)	Triangular Dist (.8, .95, 1)	Hypergeometric Dist
Salvage Costs	Distribution		
Importer Receiving	Risk Uniform(.1,1)		
Testing	Accuracy	Cost	
NIR	92%	\$10	
Relevant Outputs			
Simulation Procedure	Risk Optimizer - 1000 Iterations, 1000 Simulations		
	Testing Location		Testing Intensity
Decision Variables	Yes/No - 1/0		Test Every:Out of N
On-Farm	No - 0		N/A
Country Elevator: Receiving	Yes/No - 1/0		1:5 -5:5
Country Elevator: Loading	Yes/No - 1/0		1:5 -5:5
Export Elevator: Receiving	Yes/No - 1/0		1:5 -5:5
Export Elevator: Loading	Yes/No - 1/0		1:5 -5:5
Importer: Receiving*	Yes - 1		1:1
Output Variables	Minimum	Mean	
Expected Utility	Yes	Yes (1000 Sim)	
Additional Export Costs		Yes (1000 Sim)	
Buyer Risk		Yes (1000 Sim)	
Seller Risk		Yes (1000 Sim)	
HQ Segregated Flows		Yes (1000 Sim)	
Risk Premium		Yes (1000 Sim)	
*Importer Receiving will be not be used as a decision variable. It is assumed that importers will always test at a 1:1 rate.			

Figure 4.7. Model Specifications for Case 5.

Case - Blending NE & ND to Meet EAA Requirements			
Initial Flows of Quality			
Joint Distribution of Meeting 4 EAA requirements			
Lysine	Treonine	Tryptophan	Methionine + Cystine
0.84	0.56	0.15	0.5
Distribution of Flows - 2 Segregations			
High Quality (HQ)	Low Quality (LQ)		
Marketing Chain - ND			
On-Farm	Allow for Testing	Adventitious Commingling	Accountability
	No	None	Yes
Country Elevator			
Receiving	Yes	Elevator Comingling	Yes
Loading	Yes	Shipping Comingling	
Export Elevator			
Receiving	Yes	Elevator Comingling	Yes
Marketing Chain - NE			
On-Farm	Allow for Testing	Adventitious Commingling	Accountability
	No	None	Yes
Country Elevator			
Receiving	Yes	Elevator Comingling	Yes
Loading	Yes	Shipping Comingling	
Export Elevator			
Receiving	Yes	Elevator Comingling	Yes
Blend NE & ND			
HQ Clean	LQ Commingled in HQ	LQ Clean	HQ Diverted To LQ by Bad Testing
(NE *NE HQ Distribution + ND* ND HQ Distribution)/HQ Clean	(NE*NE LQ Distribution + ND*ND LQ Distribution)/LQ Commingled	(NE*NE LQ Distribution + ND*ND LQ Distribution)/LQ Clean	(NE *NE HQ Distribution + ND* ND HQ Distribution)/HQ Diverted
HQ = HQ Clean + LQ Commingled in HQ	LQ = LQ Clean + HQ Diverted to LQ by Bad Testing		
Loading	Yes	Shipping Comingling	
Importer			
Receiving	Yes	None	None
Testing & Model Risk Parameters			
	Commingling Rates	Accountability	Sampling Distribution
On-Farm	Triangular Dist (.001, .01, .025)	Triangular Dist (.8, .95, 1)	Hypergeometric Dist
Country Elevator	Triangular Dist (.001, .01, .025)	Triangular Dist (.8, .95, 1)	Hypergeometric Dist
Export Elevator	Triangular Dist (.001, .01, .025)	Triangular Dist (.8, .95, 1)	Hypergeometric Dist
Blending NE & ND			
Testing blends to Meet Requirements	Join Probability of Meeting Requirements		
Importer	Triangular Dist (.001, .01, .025)	Triangular Dist (.8, .95, 1)	Hypergeometric Dist
Salvage Costs			
Importer Receiving	Distribution		
	Risk Uniform(.1,1)		
Testing			
	Accuracy	Cost	
NIR	92%	\$10	
Relevant Outputs			
Simulation Procedure			
	Risk Optimizer - 1000 Iterations, 1000 Simulations		
Testing Location			
Decision Variables	Yes/No - 1/0		Testing Intensity
On-Farm	No - 0		N/A
Country Elevator: Receiving	Yes/No - 1/0		1:5 -5:5
Country Elevator: Loading	Yes/No - 1/0		1:5 -5:5
Export Elevator: Receiving	Yes/No - 1/0		1:5 -5:5
Export Elevator: Loading	Yes/No - 1/0		1:5 -5:5
Importer: Receiving*	Yes - 1		1:1
Output Variables			
	Minimum	Mean	
Expected Utility	Yes	Yes (1000 Sim)	
Additional Export Costs		Yes (1000 Sim)	
Buyer Risk		Yes (1000 Sim)	
Seller Risk		Yes (1000 Sim)	
HQ Segregated Flows		Yes (1000 Sim)	
Risk Premium		Yes (1000 Sim)	
*Importer Receiving will be not be used as a decision variable. It is assumed that importers will always test at a 1:1 rate.			

Figure 4.8. Model Specifications for Case 6.

Simulation and Optimization Procedures

The model presented here maximizes the utility by minimizing the disutility of additional testing and blending costs which include test costs, salvage costs, origin premiums, and risk premiums. The objective function is minimized by altering the decision variables: test-application locations, testing intensity, and blending proportions. The test application specifies whether a test is applied and is represented as a binary number: 1=Test and 0=No test; the test intensity specifies the frequency with which the test is applied: 1:1 (every lot sampled), 1:2 (every second lot sampled), 1:3, 1:4, and 1:5 (every fifth lot sampled).

Risk Optimizer utilizes simulation and a genetic algorithm-based optimization technique to optimize a model that contains uncertainty. Probability distribution functions representing uncertainty are utilized to define risk for specified model components and are used in a spreadsheet cell instead of a formula or number (Palisade, 1998). Within Risk Optimizer, 1,000 iterations are conducted per simulation. Utilizing the Risk Optimizer within @Risk, algorithmic searching runs 1,000 different simulations to determine the optimal testing and blending strategies. Once an optimal solution is found, @Risk is programmed to determine the mean results of 10,000 simulated draws based on random-distribution cells.

Model Variable Distributions

Triangular distributions are commonly used at various locations within the marketing chain. The distribution is used to simulate handler accountability risk and comingling risk. It is also used in some of the best-fit distributions determined by @Risk modeling. A risk triangle utilizes three points to determine the probability for random sampling: the minimum point, the maximum point, and the most likely point. The format would appear as follows:

$$\text{RiskTriang}(\text{Minimum}, \text{Most Likely}, \text{Maximum}) \quad (\text{Eq. 4.10})$$

Similarly, uniform distributions are used throughout the various models to determine random sampling. The risk uniform distribution uses a continuous distribution function to determine the random samples between a minimum and maximum area. There is no bias in likelihood of values between the upper and lower points. The format appears as follows:

$$RiskUniform(Minimum, Maximum) \quad (Eq. 4.11)$$

This distribution is used to determine the random samples of salvage costs at the export level and the premium costs of shipments taken from Nebraska in the blending case model.

CHAPTER 5: RESULTS AND ANALYSIS

Introduction

The purpose and goal of this study is to determine the optimal testing strategies that producers and handlers may employ in order to minimize the costs and risks based on purchasers' strategies. Currently, marketplace standards typically test for protein and oil, but neglect the amount of EAA present in soybeans. The following section indicates the optimal testing strategy based on disutility from the testing costs as well as the discounts and the risks imposed on sellers and buyers. The model presented in the previous chapter specifies the cases that are used and indicates which cases are analyzed to determine the effects. A base case that examines the marketing chain is used to reference the various cases that are presented. Multiple cases determine the effects that different variables and requirements have on marketing and testing strategies. Two different models are used to analyze varying strategies: one with a blending component and one without that component.

Results are reported for each case and every sensitivity that were run. The cases and sensitivities are modeled to understand the various outcomes and effects that different markets may present. Decision variables chosen through the optimization procedure indicate which strategy may be best to minimize the costs and risks for a simulated merchandiser's preference. The costs and risks associated with the varying strategies indicate the expected performance of the optimal strategies. The results of the model indicate the overall marketing-chain responses to the introduction of testing for EAA components.

The following section shows the results of running two different models: a dual-marketing system that includes the testing and segregating of soybeans that meet quality requirements, high quality, and soybeans that do not meet quality requirements, low quality. The

first case determines how the model functions when no testing is applied. The four following cases analyze the impacts of different purchasers' quality requirements and the optimal testing that results. The costs and risks are also analyzed. The sixth and final case utilizes the blending model presented in Chapter 4. Similar decision-variable outputs allow for comparisons across all cases and models that were run. Additional outputs determine the optimal testing strategies for two different supply chains as well as a blending decision variables. The costs and risks are structured similarly to aid in the comparison. It should be noted that all the cases' tables are independent of one another. The final strategy summary provides most of the discussion about the differing cases.

No Testing: Base Case

To understand the impacts of testing for EAA, a base case was established to examine the costs and risks with a market that has no testing. A simulation was used to determine the average values for the outputs of a testing strategy that utilized no testing. The testing was applied at the importer level, testing every shipment, to evaluate the ending flows of the soybeans in order to interpret results. Table 5.1 shows the results from the initial case without testing. The initial quality standards were set at protein levels of 34%, a standard level for testing soybeans. The testing costs were minimal at .02 c/bu. Average salvage costs were 4.36 c/bu. This cost was applied to low-quality lots that were tested in high-quality flows and diverted to the low-quality flows.

All costs estimated at these points were applied to all lots (5 million bu) included in the marketing chain. The total costs for salvage and testing were estimated at 4.42 c/bu. When applied to just the high-quality soybeans, the costs rose to 10.42 c/bu, resulting in buyer risks of 1.48%. This increase represented the risk that buyers face. It was the probability that importers

Table 5.1. Base Case - No Testing.

Protein Meeting Requirement - No Testing				
	34% Protein Requirement Level		33% Protein Requirement Level	
Outputs				
Costs (c/bu)	Mean	St. Dev	Mean	St. Dev
Importer Receiving Test	0.02	-	0.02	-
Total Export Test	0.02	-	0.02	-
Salvage Costs	4.36	2.54	3.71	2.00
Total Export Cost	4.42	0.93	3.73	2.00
Cost of HQ	10.24	2.18	5.71	3.07
Buyer Risk	1.48%	0.45%	0.82%	0.20%
Seller Risk	15.46%	3.93%	9.30%	2.02%
Total Buyer-Seller Risk	16.69%	4.24%	10.04%	2.18%
Probability of Meeting				
EAA Requirements	49.77%		39.60%	
Disutility & Risk Premium				
Expected Disutility	1.0130	0.0039	1.0148	0.0042
Risk Premium	1.87	1.06	2.41	1.28
Decision Variables	Test			
	Test	Intensity	Test	Intensity
Imp Rec Test*	1	1	1	1

*(Testing manually applied at importer to evaluate quality)

Table 5.2. Base Cases – Not Testing: Probability of Meeting Requirements.

Probability of Flows Meeting Requirements - 34% Protein				
	HQ		LQ	
	Mean	St. Dev	Mean	St. Dev
Initial Quality Composition	46%	N/A	54%	N/A
Farm in Bin	46%	0%	54%	0%
CE in Store	50%	2%	50%	2%
CE Loaded on Track	50%	2%	50%	2%
EE in Store	51%	2%	49%	2%
EE After Loading	51%	2%	49%	2%
Importer after Test	43%	1%	57%	1%
Probability of Flows Meeting Requirements - 33% Protein				
	HQ		LQ	
	Mean	St. Dev	Mean	St. Dev
Initial Quality Composition	69%	N/A	31%	N/A
Farm in Bin	69%	0%	31%	0%
CE in Store	72%	1%	28%	1%
CE Loaded on Track	72%	1%	28%	1%
EE in Store	72%	1%	28%	1%
EE After Loading	72%	1%	28%	1%
Importer after Test	65%	1%	35%	83%

purchased high-quality soybeans that tested as high quality and were actually low quality. It was a test failure that showed high quality while the sample was actually a low quality. The seller risk was 15.46%. This risk represented the risk that buyers will sell high-quality soybeans but importer testing may indicate that purchases are, in fact, low quality. The lack in quality was due to adventitious comingling in the shipment and a lack of identity due to less of testing at earlier locations in the supply chain.

Evaluating the final composition of high-quality lots showed that the probability of high-quality soybeans meeting the EAA requirements was 49.77%, suggesting that, by testing for protein, the importers would only meet the EAA requirement about 50% of the time if they made

purchases based on protein quality standards. The expected disutility was 1.130. This disutility represented the expected utility of grain handlers. Expected disutility cannot be interpreted as a given value, but between cases and sensitivities, it gave an indication about the grain handlers' preference. If disutility was higher, the testing system was less preferential to the grain handlers. It was also important to examine how the risk premium was affected by the disutility function. Higher disutility, generally, meant higher risk premiums. If a testing system was less preferred by grain handlers, they required a greater risk premium to incorporate the testing system. For this case, the risk premium was 1.87 c/bu, meaning that handlers would require an additional 1.87c/bu to accommodate a system that did not regularly test for protein.

The second panel of Table 5.1 shows how the results changed if the protein quality were relaxed to 33%. When the requirements are changed from 34% to 33%, there was a large difference with the outcomes. The total costs changed from 10.24 to 5.71 c/bu. This decrease due to the increased probability of meeting the high-quality requirements and the larger amount of soybeans in the high-quality flows, i.e., less cost dispersed over a great quantity of high-quality soybeans. Despite decreased average costs, the standard deviation went from 2.18 to 3.07 c/bu. Both the buyer and sellers' risks decreased from 1.48% to .82% and 15.46% to 9.30%, respectively. This decrease suggested, that when constraints are relaxed, both buyers and sellers had less risk than when the constraints are stricter. Table 5.1 indicates that, while the costs and risks may be lower for protein requirements of 33%, the expected disutility was higher for the latter case. This increase was likely due to the total amount of flows that meet the high quality.

Table 5.2 shows the percentage of flows at each stage and whether each respective flow is high or low quality. Any alterations of the quality composition would be due to adventitious comingling. The increased amount of high-quality soybeans in the 33% protein-requirement

simulation were the reason for a higher expected disutility. One point of interest was the probability of meeting the requirements for the export loading and the importer. There was a significant drop for both requirement levels to have the probability of meeting requirements. This occurred because testing is applied at the importer level. At this point, testing indicated which lots were low quality, diverting them into the low-quality streams and discounting them appropriately.

Testing for Protein

The second case is designed to determine the effects of a testing system for the protein requirements. Table 5.3 illustrates the optimal testing strategy for each case sensitivity that was run. Also included is the composition at each stage in the supply chain. The results indicate that the best strategy is to test at every location except for the country-elevator receiving point. For the country-elevator loading test as well as the export-elevator loading, an intensity of 5 is the optimal decision. This intensity means that 1 of every 5, or 20%, of all shipments will be tested. At the export elevator testing point, it is best to test 1 of every 1 shipments, 100%, that are exported. The importers are testing every shipment at a 1:1 ratio.

Costs, risks, and disutility are reported in Table 5.4. The optimization procedure shows that the minimum disutility comes back at 1.0048, resulting in total high-quality testing costs of 2.03 c/bu. Subsequently, the buyer and seller's risks are .26% and 3.17%, respectively. These risks would indicate that, when testing for protein within the supply chain, buyers would purchase a shipment, thinking it is high quality when it is actually low quality .26% of the time. The sellers' shipment would be rejected 3.17% of the time even though it tested as high quality.

The risk premium is described as the additional premium that system integrators pay to incur additional risks and the subsequent costs from investing in additional testing for the entire

Table 5.3. Case 2 – Testing Protein: Optimal Testing Strategies.

Testing for Protein Only	Initial Test		Sensitivity 1:		Sensitivity 2:		Sensitivity 3:		Sensitivity 4:	
	Protein	34%	Protein	33%	Testing	50.00	Testing	87.5%	Salvage Costs	.75-1.5
Probability of Flows Meeting Requirements										
	HQ	LQ	HQ	LQ	HQ	LQ	HQ	LQ	HQ	LQ
Initial Quality Composition	46%	54%	69%	31%	46%	54%	46%	54%	46%	54%
Farm in Bin	46%	54%	69%	31%	46%	54%	46%	54%	46%	54%
CE in Store	50%	50%	72%	28%	50%	50%	50%	50%	50%	50%
CE Loaded on Track	45%	55%	68%	32%	50%	50%	45%	55%	45%	55%
EE in Store	41%	59%	65%	35%	45%	55%	41%	59%	41%	59%
EE After Loading	36%	64%	61%	39%	39%	61%	39%	61%	40%	60%
Importer after Test	35%	65%	59%	41%	38%	62%	38%	62%	39%	61%
Probability of Flows Meeting EAA Requirements										
	49.60%		39.46%		49.66%		49.59%		49.66%	
Decision Variables	Test	Intensity	Test	Intensity	Test	Intensity	Test	Intensity	Test	Intensity
CE Rec Test	0	N/A	0	N/A	0	N/A	0	N/A	1	1:5
CE Load Test	1	1:5	1	1:5	0	N/A	1	1:5	1	1:5
Exp Rec Test	1	1:5	1	1:5	1	1:5	1	1:1	1	1:5
Exp Load Test	1	1:1	1	1:1	1	1:1	1	1:1	1	1:1
Imp Rec Test*	1	1:1	1	1:1	1	1:1	1	1:1	1	1:1
*(Importer testing manually adjusted to 1:1)										

Table 5.4. Case 2 – Testing Protein: Costs and Risks.

Testing for Protein Only	Initial Test	Sensitivity 1:	Sensitivity 2:	Sensitivity 3:	Sensitivity 4:
	Protein 34%	Protein 33%	Testing 50	Testing 87.5%	Salvage Costs .75-1.5
Outputs					
Costs					
CE Receiving Test	N/A	N/A	N/A	N/A	N/A
CE Loading Test	0.03	0.04	N/A	0.03	0.03
EE Receiving Test	0.03	0.04	0.16	0.14	0.14
EE Loading Test	0.01	0.02	0.07	0.01	0.01
Importer Receiving Test	0.01	0.02	0.06	0.01	0.01
Total Export Test	0.08	0.12	0.28	0.20	0.20
Salvage Costs	0.63	0.77	0.68	0.53	0.99
Total Export Cost	0.71	0.89	0.97	0.72	1.18
Cost of HQ	2.04	1.51	1.89	2.56	3.07
Risks					
Buyer Risk	0.26%	0.19%	0.26%	0.31%	0.18%
Seller Risk	3.17%	2.30%	3.19%	2.45%	2.22%
Total Buyer-Seller Risk	3.42%	2.49%	3.44%	2.76%	2.40%
Disutility & Risk Premium					
Expected Disutility	1.0048	1.0070	1.0059	1.0051	1.0066
Risk Premium	0.25	0.52	0.36	0.27	0.45

systems. In this case, a risk premium of .25 c/bu indicates that grain handlers require an additional quarter of a cent per bushel to make up for the additional protein-value testing. Sampling distributions for the EAA quality of soybeans that meet the protein requirements also give insight about the EAA preferences that purchasers may want. Evaluating importer flows after testing shows that, based on testing for protein at 34%, high-quality lots would meet EAA preferences 49.60% of the time, as reported in Table 5.4. This likelihood would indicate that, by testing for protein, importers would expect to meet the EAA requirements 49.60% of the time.

Further analysis of the sensitivities shows the impacts that changing important variables may have on the costs and risks. The first sensitivity adjusts the protein requirements. Current marketplace measurements evaluate protein at the 34% level and accept shipments down to 33%. If the requirements are relaxed to 33%, we see a slight drop in costs and risks, as is expected.

Optimization results indicate that testing would be no different. Buyer risks would drop from .26% to .19%, and seller risks would decline from 3.17% to 2.30%. The total costs of high-quality shipments would decline about half a cent to 1.51 c/bu. Overall disutility increases to 1.007, likely due to the increased total ending flows that now meet the 33% protein requirement. Grain handlers would also require a higher risk premium of .52 c/bu. It is interesting that risk premiums would increase here even though the buyer and seller's risk decreases. The reasoning behind this decrease is the fact that the overall high-quality flows increase. Even though risks go down, the total amount of high-quality flows that have a risk of misidentification increases, which increases the monetary value at risk. Consider that the risk premium identifies the monetary indifference based on total risk, which increases as high-quality probabilities and flows do.

When testing costs are increased from 10 per test to 50, the testing strategies are altered. The best decisions for testing (Table 5.3) show that less testing is optimal. Testing should only be conducted at the export and import terminals, testing every 5th unit at export receiving and every unit at the loading and importer receiving. Results from this strategy show about a half-cent, high-quality cost increase from the base case. Buyer risks remain constant at .26%, but seller costs increase slightly from 3.17% to 3.19%. The total expected disutility also increases from 1.0048 to 1.0059; the risk premium increases by .11 c/bu. Although testing is increased, risks are effected minimally while costs increase by a small portion. Sampling the end-quality lots shows that the probability of meeting the EAA requirements only increases slightly by .06%.

Adjusting the testing from 92% accuracy to 87.5% only changes the testing at the export receiving location compared to the base case. Intensity is increased to test every shipment that is received. This increase causes an increase of .52 c/bu for high-quality lots. Interestingly, buyer risks increase from .26% to .31% while seller risks diminish from 3.17% to 2.45%, indicating that superior testing is more beneficial to buyers. Further analysis shows that the overall disutility increases by .0003 and that the risk premium increases by .02 c/bu, both relatively small changes. The final sensitivity conducted examines the effects of elevated salvage costs. The overall costs for high-quality soybeans increase to 3.07 c/bu while the risks for buyers and sellers decrease to .18% and 2.22%, respectively. Disutility and risk premiums also increase to 1.0066 and .45.

Overall, sensitivities responded as anticipated. When requirements are relaxed, costs and risks decreased. However, grain handlers required a greater premium because the risk premium more than doubled. This increased premium would likely be in response to the amount of importer flows being much greater than when the requirements were higher; a much larger

portion of high-quality lots would mean that grain handlers had a much greater stake in merchandising higher-quality soybeans. As the costs increased, the testing strategies were adjusted, and the overall costs were lower than if testing remained at 10; risks did increase, but only to a small degree.

Sensitivities to salvage costs had the greatest effect on the results. While testing strategies were only adjusted at export receiving, the costs for high-quality soybeans increased by 1.03 c/bu. A decrease for both the buyer and seller's risk by about 1% suggested that strategy alterations may have lowered the overall risk of bad testing. The response to increased salvage costs would imply that handlers were very sensitive when the rejection costs increased and were willing to spend more on testing than if the penalties for not meeting the requirements were diminished. This reaction may suggest that a system of discounts would motivate grain handlers to test more strictly. Increased salvage costs also illustrated a .20 c/bu rise for the risk premium. This increase would suggest that, while soybean handlers are sensitive to salvage costs, they would require a larger premium to compensate for increased costs.

Testing for Protein and Oil

Testing for protein adds a fair amount of value, however, the market carries value in the oil content of soybeans. Simulations were run to determine the effects of testing for both protein and oil. Table 5.5 shows the optimal testing strategies for joint protein and oil testing. The initial testing (separate from the base case) checked for the minimum requirements of 33% for protein and 18% for oil. Initial flows were represented as the joint probability of meeting both requirements and are listed in Table 5.5 along with the composition of flows at receiving and loading, and export-elevator receiving locations. Table 5.6 shows the costs and risks. At the

Table 5.5. Case 3 – Testing Protein and Oil: Optimal Testing Strategies.

Testing for Protein & Oil	Initial Test		Sensitivity 1:		Sensitivity 2:		Sensitivity 3:		Sensitivity 4:	
	Protein		Protein		Testing		Testing		Salvage Costs	
	33%	18%	34%	18.5%	50.00		87.5%		.75-1.5	
Probability of the Flows Meeting the Requirements										
	HQ	LQ	HQ	LQ	HQ	LQ	HQ	LQ	HQ	LQ
Initial Quality Composition	32%	68%	12%	88%	32%	68%	32%	68%	32%	68%
Farm in Bin	32%	68%	12%	88%	32%	68%	32%	68%	32%	68%
CE in Store	32%	68%	12%	88%	38%	62%	32%	68%	32%	68%
CE Loaded on Track	28%	72%	9%	91%	32%	68%	28%	72%	28%	72%
EE in Store	25%	75%	6%	94%	27%	73%	25%	75%	25%	75%
EE After Loading	21%	79%	4%	96%	23%	77%	22%	78%	24%	76%
Importer after Test	20%	80%	4%	96%	22%	78%	21%	79%	23%	77%
Probability of Flows Meeting EAA Requirements										
	43.64%		50.32%		43.55%		43.44%		43.60%	
Decision Variables	Test	Intensity	Test	Intensity	Test	Intensity	Test	Intensity	Test	Intensity
CE Rec Test	1	1:5	1	1:5	0	N/A	1	5	1	1:5
CE Load Test	1	1:5	1	1:5	1	1:5	1	5	1	1:5
Exp Rec Test	1	1:5	1	1:5	1	1:5	1	2	1	1:1
Exp Load Test	1	1:1	1	1:1	1	1:1	1	1	1	1:1
Imp Rec Test*	1	1:1	1	1:1	1	1:1	1	1	1	1:1
*(Importer testing manually adjusted to 1:1)										

Table 5.6. Case 3 – Testing Protein and Oil: Costs and Risks.

Joint Testing for Protein and Oil	Initial Test		Sensitivity 1		Sensitivity 2	Sensitivity 3	Sensitivity 4
	Protein	Oil	Protein	Oil	Testing	Accuracy	Salvage
	33%	18%	34%	18.5%	20.00	87.50%	Uniform .75-1.5
Costs							
CE Receiving Test		0.09		0.05	N/A	0.09	0.09
CE Loading Test		0.02		0.01	0.12	0.02	0.02
EE Receiving Test		0.02		0.01	0.10	0.04	0.02
EE Loading Test		0.01		0.00	0.04	0.01	0.01
Importer Receiving Test		0.01		0.00	0.04	0.01	0.01
Total Export Test		0.15		0.07	0.29	0.17	0.15
Salvage Costs		0.43		0.36	0.51	0.49	0.88
Total Export Cost		0.58		0.43	0.80	0.66	1.03
Cost of HQ		2.04		17.13	3.70	3.24	5.19
Risks							
Buyer Risk		0.32%		2.09%	0.34%	0.54%	0.32%
Seller Risk		3.78%		19.20%	4.06%	4.14%	3.78%
Total Buyer-Seller Risk		4.09%		20.74%	4.39%	4.66%	4.08%
Disutility & Risk Premium							
Expected Disutility		1.0033		1.0011	1.0041	1.0036	1.0045
Risk Premium		0.12		0.01	0.17	0.14	0.21

export elevator loading and the import every load was tested, resulting in total testing costs of .15 c/bu and .58 c/bu, respectively, for salvage costs as applied to all lots. When costs were only applied to those soybeans meeting the requirements, the cost was 2.04 c/bu. Buyer were exposed to .36% risk, meaning that they would accept soybeans that were low quality but tested as meeting high quality .36% of the time. Seller risk was 3.78%, which meant that the sellers rejected soybeans that met the requirements but were misidentified as low quality 3.78% of the time. The grain handlers' expected disutility was optimized at 1.0033 and required a .12 c/bu risk premium to incur the additional costs and risks of testing for the protein and oil content.

Sensitivities were applied to determine the effects of changing the requirements, testing costs and accuracies, and salvage costs due to soybeans not meeting the importer's specifications. When the requirements increased to 34% for protein and 18.5% for oil, the testing costs for high quality had a large increase from 2.04 c/bu to 17.13 c/bu. Risks for the buyers and sellers had a similarly large increase. Buyer risk increased to 2.09% while the seller's risk increased to 19.20%. Expected disutility decreased to 1.0011, and the risk premium decreased to .01 c/bu. Only 12.34% of the flows met the requirements when the requirements were intensified. Low probabilities of meeting requirements was a major contributing factor with the large increases for costs and risks. While the testing was relatively cheap, very few flows of high-quality soybeans were actually being tested. When costs were applied to the smaller population of high-quality flows, the cost per bushel increased dramatically. Increase in costs was also true for risks, where a small amount of adventitious comingling may result in a great portion of soybeans being low quality in high-quality flows. High level of low-quality in high-quality flows in turn, created greater risks. Lower risk premiums may result because of decreased overall testing costs due to smaller amounts of soybeans in high-quality flows.

When testing costs are increased to \$50, the optimal testing strategies are the same, except for the country-elevator receiving location where there is no testing at all. Higher testing costs results in increased costs of 3.70 c/bu for high-quality soybeans, an increase of 1.66 c/bu from the base case. Buyer risk increases by a small margin to .34%. Seller risk increases by a larger margin (.28%) to 4.06%. The increase is likely due to the lack of testing at the country-elevator level. Expected disutility increases to 1.0041, and risk premiums increase to .17 c/bu. When testing is lowered to 87.5% accuracy, the optimal testing strategies are only altered at the export elevator where every 2nd load is tested rather than every 5th load as in the base case. Costs increase by 2.22 c/bu to 4.26 c/bu for high-quality soybeans. Risks for the buyers and sellers increase from .32% to .54% and 3.78% to 4.06%, respectively. The final sensitivity increases the salvage costs from a uniform distribution of 0.10-1.00 to 0.75-1.50. The only change for optimal testing strategies increases the testing at the export-elevator receiving location where every load is tested rather than every 5th load. The total costs for high-quality soybeans increase from 2.04 c/bu to 4.26 c/bu. The buyer and seller's risks both decrease; the buyer's risk goes to .23% and seller's risk to 2.85%.

All sensitivities conducted had similar results as the protein testing case. However, the first sensitivity deviated and showed drastic changes. The probability of jointly meeting protein and oil content requirements of 34% and 18.5% was much lower than soybeans that meet the 33% and 18% requirements. The large drop in high-quality flows spiked the marketing chain's costs and risks, and would suggest that, if enough soybeans did not meet the minimum quality requirements, the costs and risks may not be too great for buyers and sellers to implement any quality testing. Some importers took a policy to not import from certain export facilities due to a lack of quality, and these results may indicate market risk factors that dissuade importers from

doing so. Further analysis, consistent with the protein testing case, showed that increased salvage costs had an impact on testing. Beyond increased requirements, increased salvage costs had the largest impact on testing costs. Both the buyer and seller risks also decreased.

Testing for a Single EAA: Lysine

The fourth testing case is used to determine the optimal strategies if only a single EAA variable is being tested. In this case, the model determines the optimal testing for lysine values. Table 5.7 shows the optimal testing strategies for lysine. The costs and risks are reported in table 5.8. The probabilities of meeting the lysine requirements are also shown. One interesting point to note is that, based on soybean quality sampling, all soybean samples meet the lysine requirements.

Despite all lots meeting the requirements, there are testing errors that may occur and cause some lots to be misrepresented as low quality when they are, in fact, high quality. Testing errors leads to not all soybeans meeting the requirements at the end of the supply chain. Optimal testing strategies show that the best testing strategy is to only check at the export loading and import receiving while testing every load that comes through these locations. This strategy results in total costs of 1.04 c/bu for all lots and 1.11 c/bu for all high-quality soybeans that are coming through the elevators. The resulting risks are minimal, with buyer risk at only .15% and seller risk at 1.86%. These risks results in an expected disutility of 1.0095, and the risk premium is .98 c/bu.

Sensitivities were applied to testing costs, accuracies, and salvage costs. Other models track changes when the requirements are altered, however, if the lysine requirements are relaxed, there is no change for the amount of soybeans that meet those requirements, and sensitivities were not included. When testing costs were increased, there were no changes to the optimal

Table 5.7. Case 4 – Testing for a Single EAA: Optimal Testing Strategies.

Testing for One Amino Acid	Initial Test		Sensitivity 1		Sensitivity 2		Sensitivity 3	
	Lysine .84		Testing 50		Accuracy 87.5%		Salvage Costs .75-1.5	
Probability of the Flows Meeting the Requirements								
	HQ	LQ	HQ	LQ	HQ	LQ	HQ	LQ
Initial Quality Composition	100%	0%	100%	0%	100%	0%	100%	0%
Farm in Bin	100%	0%	100%	0%	100%	0%	100%	0%
CE in Store	100%	0%	100%	0%	100%	0%	100%	0%
CE Loaded on Track	100%	0%	100%	0%	100%	0%	100%	0%
EE in Store	100%	0%	100%	0%	100%	0%	98%	2%
EE After Loading	96%	4%	96%	4%	96%	4%	94%	6%
Importer after Test	94%	6%	94%	6%	94%	6%	92%	8%
Decision Variables	Test	Intensity	Test	Intensity	Test	Intensity	Test	Intensity
CE Rec Test	0	N/A	0	N/A	0	N/A	0	N/A
CE Load Test	0	N/A	0	N/A	0	N/A	0	N/A
Exp Rec Test	0	N/A	0	N/A	0	N/A	1	1:5
Exp Load Test	1	1:1	1	1:1	1	1:1	1	1:1
Imp Rec Test*	1	1:1	1	1:1	1	1:1	1	1:1
*(Importer testing manually adjusted to 1:1)								

Table 5.8. Case 4 – Testing for a Single EAA: Costs and Risks.

Testing for Protein Only	Initial Test	Sensitivity 1	Sensitivity 2	Sensitivity 3
	Lysine .84	Testing \$50	Testing 87.5%	Salvage .75-1.5
Costs				
CE Receiving Test	N/A	N/A	N/A	N/A
CE Loading Test	N/A	N/A	N/A	N/A
EE Receiving Test	N/A	N/A	N/A	0.06
EE Loading Test	0.03	0.15	0.03	0.03
Importer Receiving Test	0.03	0.15	0.03	0.03
Total Export Test	0.06	0.30	0.06	0.12
Salvage Costs	0.98	0.98	1.08	1.93
Total Export Cost	1.04	1.28	1.14	2.05
Cost of HQ	1.11	1.36	1.21	2.23
Risks				
Buyer Risk	0.15%	0.15%	0.26%	0.15%
Seller Risk	1.86%	1.86%	2.05%	1.83%
Total Buyer-Seller Risk	2.01%	2.01%	2.30%	1.97%
Disutility & Risk Premium				
Expected Disutility	1.0095	1.0106	1.0099	1.0135
Risk Premium	0.98	1.20	1.07	1.89

testing strategies, but the costs did increase. High-quality costs increased from 1.11 c/bu to 1.36 c/bu. The buyer and seller risks were not affected either, but the expected disutility increased 1.0106 while the risk premium increased by .22 c/bu. An increased risk premium would mean that grain handlers expected to be compensated higher if the testing costs rose. When testing accuracies decreased to 87.5%, there was still no difference with the optimal testing strategies. The total costs increased, but not to the extent of the higher testing cost. There were no increases for the total testing costs, but the salvage costs increased due to a less accurate test.

Risks also increased; the buyer's risk increased to .26%, and the seller's risk rose to 2.05%. Expected disutility increased to 1.0099, and the risk premium increased to 1.07 c/bu. As other cases have shown, salvage costs altered the optimal testing strategy the most. If salvage costs increased, additional testing was imposed at the exporter-receiving level. The best strategy at this location was to test every 5th unit. More intense testing increased high-quality costs by 1.12 c/bu, making them 2.23 c/bu. Increased salvage costs also altered the total risks. While buyer risk was unaffected, seller risk decreased to 1.83%. The expected disutility increased to 1.0135, and the risk premium increased to 1.89 c/bu.

Ultimately, sensitivities performed the same way as the other cases. However, all flows meeting the specifications altered the results to a large degree. Larger flows for the high-quality soybeans increased the expected disutility because there was an increase for the overall high-quality portion of the disutility function, which had additional costs. This concept can be more easily seen with the risk premium, which is significantly higher. Because there was a large portion of the flow susceptible to risk, handlers expected higher costs. Thus, handlers would require a higher premium for incurring the increased costs. Like other cases, grain handlers were sensitive to salvage costs and responded more than they did with other sensitivities. Handlers also required a higher premium for the increased salvage costs.

Testing for All EAAs

The final case for the testing model examines the impacts of EAA requirements. There are a total of five EAAs, however, only four requirements are met; methionine and cysteine are measured as if one could replace the other. Thus, the sum of the methionine and cysteine EAA must meet one requirement. Table 5.9 shows the results for the optimal testing solution along with the likelihood for the flows to meet the minimum EAA requirements. The base case uses

EAA requirements for growing hogs from 75-100 kg. The likelihood that these requirements are met is 27% at the initial point in the marketing chain. From there, adventitious comingling a subsequent diversion diminish the composition to just 15% at the importer level. This composition is based on a strategy that tests at every location. At the country-elevator receiving level, it is best to test every 5th load received. This is the same intensity used at the country-elevator loading and export-elevator receiving. For the exporter loading and importer receiving, it is best to test every unit.

The costs and risks are reported in Table 5.10. Overall testing applied to all lots results in total costs of .50 c/bu. When only applied to the high-quality lots, costs are roughly 3.39 c/bu. The risks for buyers are .37% while risks for sellers are 4.41%. Expected disutility is recorded at 1.0027, and the risk premium is .08 c/bu. The applied sensitivities cause similar changes to the results as other cases have shown. When the requirements are shifted to hog weights of 100-130 kg, the likelihood of meeting the requirements increases to 91%. This optimal testing strategy results so that no testing is done at the country-elevator level. All other testing locations remain the same, and the intensities are not adjusted at all. This strategy decreases the overall costs by 2.17 c/bu for all high-quality soybeans. While the overall costs decrease, salvage costs increase, which indicates that larger flows are high-quality and less are low-quality soybeans. Seller risk decreases from 4.41% to 1.94%. The expected disutility increases to 1.0088. The risk premium also increases to .84 c/bu.

An increased testing cost has a smaller effect than relaxed requirements. The best-case testing strategy is only altered at the country-elevator level where there is no testing. All other testing and intensities remain the same. Overall, the costs for high-quality soybeans increase by .66 c/bu to 4.05 c/bu. The risks remain relatively stable, however, the seller's risk increases

Table 5.9. Case 5 – Testing for All EAA: Optimal Testing Strategies.

Testing for All EAAs	Initial Test		Sensitivity 1		Sensitivity 2		Sensitivity 3		Sensitivity 4	
	Hogs 75-100kg		Hogs 100-135kg		Costs 50.00		Accuracy 87.5%		Salvage Costs .75-1.5	
Probability of the Flows Meeting the Requirements										
	HQ	LQ	HQ	LQ	HQ	LQ	HQ	LQ	HQ	LQ
Initial Quality Composition	27%	73%	91%	9%	27%	73%	27%	73%	27%	73%
Farm in Bin	27%	73%	91%	9%	27%	73%	27%	73%	27%	73%
CE in Store	27%	73%	92%	8%	33%	67%	27%	73%	27%	73%
CE Loaded on Track	23%	77%	92%	8%	27%	73%	23%	77%	23%	77%
EE in Store	20%	80%	89%	11%	22%	78%	19%	81%	20%	80%
EE After Loading	16%	84%	85%	15%	18%	82%	17%	83%	16%	84%
Importer after Test	15%	85%	83%	17%	17%	83%	16%	84%	15%	85%
Decision Variables	Test	Intensity	Test	Intensity	Test	Intensity	Test	Intensity	Test	Intensity
CE Rec Test	1	1:5	0	N/A	0	N/A	1	1:5	1	1:5
CE Load Test	1	1:5	0	N/A	1	5	1	1:5	1	1:5
Exp Rec Test	1	1:5	1	5	1	5	1	1:2	1	1:5
Exp Load Test	1	1:1	1	1:1	1	1:1	1	1:1	1	1:1
Imp Rec Test*	1	1:1	1	1:1	1	1:1	1	1:1	1	1:1

Table 5.10. Case 5 – Testing for All EAAs: Costs and Risks

Testing for All EAAs: 4 Requirements	Initial Test	Sensitivity 1	Sensitivity 2	Sensitivity 3	Sensitivity 4
	Hog Wt 70-100	Hog Wt 100 +	Testing 50	Testing 87.5%	Salvage .75-1.5
Costs					
CE Receiving Test	0.08	N/A	N/A	0.08	0.08
CE Loading Test	0.02	N/A	0.10	0.02	0.02
EE Receiving Test	0.01	0.06	0.09	0.04	0.01
EE Loading Test	0.01	0.03	0.03	0.01	0.01
Importer Receiving Test	0.00	0.03	0.03	0.01	0.00
Total Export Test	0.12	0.11	0.25	0.15	0.12
Salvage Costs	0.38	0.91	0.43	0.41	0.77
Total Export Cost	0.50	1.01	0.67	0.56	0.89
Cost of HQ	3.39	1.22	4.05	3.59	6.05
Risks					
Buyer Risk	0.37%	0.16%	0.37%	0.60%	0.37%
Seller Risk	4.41%	1.94%	4.43%	4.56%	4.40%
Total Buyer-Seller Risk	4.76%	2.10%	4.79%	5.13%	4.76%
Disutility & Risk Premium					
Expected Disutility	1.0027	1.0088	1.0033	1.0029	1.0036
Risk Premium	0.08	0.84	0.11	0.09	0.13

slightly to 4.43%. Expected disutility increases slightly to 1.0033 as well. The risk premium also increases slightly to .11 c/bu. When adjusting the testing accuracies, the outcomes are similar to what they were for the other cases. The total cost of high-quality soybeans increases by .20 c/bu.

The buyer and seller's risks also increase. The buyer's risk increases significantly to .60%, and the seller's risk increases to 4.56%. While the increase in risks are not large, it is still worth noting This change in risks causes the expected disutility to increase to 1.0029. The risk premium increases, minimally, to .09 c/bu. Increasing salvage costs have no effect on the optimal testing strategies, however, the costs and risks are altered. The total costs for high-quality soybeans are 6.05 c/bu, an increase of 2.66 c/bu. The risks remain more or less the same. Overall expected disutility is 1.0036, an increase of .0011, and also results in an increase of the risk premium to 0.13.

Overall, adjusting both the requirements and salvage costs have the greatest impacts on outputs. Adjusting the EAA requirements has the largest effect on testing strategies. Initial flows are increased to 90.98%, and less testing is needed. Because of the increased high-quality flows, the risks decrease by over half. However, due to this increase in high-quality soybeans, the grain handlers require a much higher premium for both the high-quality and low-quality soybeans. Grain handlers are very sensitive to what the importers and end users require in terms of EAA quality. Stricter requirements increase the testing costs and the overall costs for high-quality soybeans, but lax requirements diminish the overall risks that sellers and buyers face. Increased salvage costs also have a substantial effect on the costs of high-quality soybeans. Unlike other cases, the risks are not affected, but costs increase. This increase comes directly from the increased salvage costs for high-quality flows that are diverted from high-quality to low-quality streams.

Table 5.11. HQ Lots Meeting All EAA Requirements.

	Case 1	Case 2	Case 3	Case 4	Case 5
Testing Method	No Testing	Protein	Protein & Oil	Lysine	All EAA
Likelihood of HQ Meeting the EAA Requirements	48.87%	49.65%	43.64%	26.88%	99.90%

Testing for various quality traits results in different likelihoods that the EAA requirements are met. Table 5.11 shows the different testing methods and the likelihood that those methods allow the EAA requirements to be met. Testing for all EAAs is obviously the best method to ensure that the EAA requirements are met. What is interesting is that testing simply for lysine has the lowest probability for all EAA requirements to be met. This is likely due to the fact that nearly 100% of all soybeans meet lysine requirements. This results in distributions of soybeans tested for lysine that mimic the entire lot; they are the same distribution.

Testing and Blending Model

The final case has different results than the previous five cases. Chapter 4 outlines the additional decision variables. More testing decision variables are added for the Nebraska sub-chain. There is also an additional blending-decision variable added. It should be noted that blending is a common practice for the market. Sellers incorporate two different origins when shipping to purchasers in order to ensure that the quality requirements are met. Generally, blending is done in proportions, e.g., four shipments from North Dakota and one from Nebraska, depending on the sellers' strategies to improve quality. Decisions are made to minimize costs as well as to improve the quality consistency and minimize the risk of rejection.

The base case results in the testing strategies shown in Table 5.12. The best strategy for the base case is to test at all locations in both the North Dakota and Nebraska supply chains. All locations test every 5th shipment, except for the Nebraska export-loading location and the

importer receiving. The blending-decision variable shows that 86% of the shipments should be from North Dakota and that 14% should be from Nebraska, meaning that, if a total of 10 million bushels were shipped, 8.6 million bushels would originate from North Dakota while 1.4 million bushels would originate from Nebraska. Blending at this ratio would result in EAA requirements being met 99.1% of the time after blending. Table 5.13 shows the probability of meeting the requirements post-blend along with the costs of testing and blending. The additional costs for high-quality soybeans are 5.20 c/bu. These costs includes testing from each sub-chain and the additional premium added to Nebraska shipments. Buyer risk, as a result from blending, is .36%, and seller risk is 4.66%. The total expected disutility is 1.0045, and grain handlers expect a .21 c/bu risk premium to be indifferent to handling and testing two different quality flows. shipment is tested when loading.

At the export elevator, every unit is tested when received. In the North Dakota sub-chain, the country-elevator loading and export-elevator receiving test every 5th unit. After blending, export loading test every 5th unit, and importers test every shipment that they receive. Blending proportions change minimally with 87% originating from North Dakota and 13% from Nebraska. This blending combination will result in the EAA requirements being met 99.81% of the time. The total costs increase as well. The costs of high-quality soybeans increase to 5.75 c/bu. The total costs for North Dakota soybeans increase to 3.00 c/bu, and Nebraska soybeans increase to 9.81 c/bu. Although the costs increase, the buyer and seller's risks decrease to .34% and 4.09%, respectively. Expected disutility increases to 1.0052, however, the risk premium does not increase or decrease. When testing accuracies decrease, testing is still applied at each location, however, the intensities are altered. In the North Dakota sub-chain, testing at the country-elevator loading increases to test every 4th shipment rather than every 5th shipment. In the

Table 5.12. Case 6 – Testing and Blending for EAA: Costs and Risks.

Testing for All EAAs	Initial Test		Sensitivity 1		Sensitivity 2	
	Hog Wt 70-100		Hog Wt 100-135		Testing Costs 50	
Costs	North Dakota	Nebraska	North Dakota	Nebraska	North Dakota	Nebraska
CE Receiving Test	0.25	0.12	1.25	-	1.25	-
CE Loading Test	0.06	0.03	0.30	0.25	0.30	0.25
EE Receiving Test	0.06	0.34	0.31	1.69	0.31	1.69
Total Costs Pre-Blend	0.60	0.74	3.00	2.31	3.00	2.31
Origin Premium	-	7.50	-	7.50	-	7.50
Total HQ Costs - ND/NE	0.60	7.82	3.00	10.10	3.00	9.81
HQ Costs Blended	2.45		4.58		4.58	
EE Loading Test	0.01		0.03		0.03	
Importer Receiving Test	0.03		0.15		0.15	
Total Export Test	2.71		5.18		5.18	
Salvage Costs	2.50		2.48		2.48	
Total Export Cost	1.05		7.65		7.65	
Cost of HQ	5.20		1.54		1.54	
Risks						
Buyer Risk	0.36%		0.36%		0.36%	
Seller Risk	4.31%		4.31%		4.29%	
Total Buyer-Seller Risk	4.66%		4.66%		4.64%	
Disutility & Risk Premium						
Expected Disutility	1.0045		1.0045		1.0045	
Risk Premium	0.21		0.21		0.21	
Blending Quality Results						
Lysine	1.19	1.10	1.19	1.10	1.19	1.10
Threonine	0.69	0.69	0.69	0.69	0.69	0.69
Tryptophan	0.22	0.20	0.22	0.20	0.22	0.20
Methionine + Cysteine	0.52	0.46	0.52	0.46	0.52	0.46
Blending Requirements Met	99.90%		99.90%		99.90%	

Table 5.12. Case 6 – Testing and Blending for EAA: Costs and Risks. (Continued)

Testing for All EAAs (Continued)	Sensitivity 4		Sensitivity 5	
	Testing Accuracy 87.5%		Salvage Costs .75-1.50	
Costs	North Dakota	Nebraska	North Dakota	Nebraska
CE Receiving Test	0.25	0.12	0.25	0.12
CE Loading Test	0.06	0.03	0.06	0.03
EE Receiving Test	0.06	0.34	0.06	0.34
Total Costs Pre-Blend	0.60	0.74	0.60	0.74
Origin Premium	-	7.50	-	7.50
Total HQ Costs - ND/NE	0.60	7.82	0.60	7.82
HQ Costs Blended	2.45		2.45	
EE Loading Test	0.01		0.01	
Importer Receiving Test	0.03		0.03	
Total Export Test	2.71		2.71	
Salvage Costs	2.50		2.50	
Total Export Cost	1.05		1.05	
Cost of HQ	5.20		5.20	
Risks				
Buyer Risk	0.36%		0.36%	
Seller Risk	4.31%		4.31%	
Total Buyer-Seller Risk	4.66%		4.66%	
Disutility & Risk Premium				
Expected Disutility	1.0045		1.0045	
Risk Premium	0.21		0.21	
Blending Quality Results				
Lysine	1.19	1.10	1.19	1.10
Threonine	0.69	0.69	0.69	0.69
Tryptophan	0.22	0.20	0.22	0.20
Methionine + Cysteine	0.52	0.46	0.52	0.46
Blending Requirements Met	99.90%		99.90%	

Table 5.13. Testing and Blending for All EAA.

Testing And Blending for All EAA	Base Case				Sensitivity 1				Sensitivity 2			
	Hogs 75-100kg				Hogs 75-100kg				Testing \$50			
Probability of the Flows Meeting the Requirements												
	North Dakota		Nebraska		North Dakota		Nebraska		North Dakota		Nebraska	
	HQ	LQ			HQ	LQ			HQ	LQ		
Initial Quality Composition	27%	73%	45%	55%	91%	9%	97%	3%	27%	73%	45%	55%
Farm in Bin	27%	73%	50%	50%	91%	9%	N/A	N/A	27%	73%	50%	50%
CE in Store	27%	73%	45%	55%	92%	8%	N/A	N/A	33%	67%	45%	55%
CE Loaded on Track	23%	77%	41%	59%	92%	8%	N/A	N/A	26%	74%	41%	59%
EE in Store - Pre Blend	20%	80%	38%	62%	89%	11%	N/A	N/A	22%	78%	38%	62%
	Blended				Blended				Blended			
Blended	22%	78%			22%	78%			24%	76%		
EE At Loading - Blended	21%	79%			21%	79%			23%	77%		
Importer after Test	20%	80%			21%	79%			22%	78%		
Decision Variables	Test	Intensity	Test	Intensity	Test	Intensity	Test	Intensity	Test	Intensity	Test	Intensity
CE Rec Test	1	5	1	5	0	N/A	N/A	N/A	0	N/A	1	5
CE Load Test	1	5	1	5	0	N/A	N/A	N/A	1	5	1	3
Exp Rec Test	1	5	1	1	1	5	N/A	N/A	1	5	1	1
Blending Portions	86%		14%		100%		0%		87%		13%	
	Blended Testing				Blended Testing				Blended Testing			
Exp Load Test	1	5			1	1			1	5		
Imp Rec Test*	1	1			1	1			1	1		

Table 5.13. Testing and Blending for All EAA. (Continued)

Testing and Blending for All EAAs (Continued)	Sensitivity 3				Sensitivity 4			
	Testing Accuracy 87.5%				Salvage Costs \$.75-\$1.5			
Probability of the Flows Meeting the Requirements								
	North Dakota		Nebraska		North Dakota		Nebraska	
	HQ	LQ			HQ	LQ		
Initial Quality Composition	27%	73%	45%	55%	27%	73%	45%	55%
Farm in Bin	27%	73%	50%	50%	27%	73%	50%	50%
CE in Store	27%	73%	45%	55%	27%	73%	45%	55%
CE Loaded on Track	23%	77%	41%	59%	23%	77%	41%	59%
EE in Store - Pre Blend	20%	80%	38%	62%	20%	80%	40%	60%
	Blended				Blended			
Blended	23%	77%			23%	77%		
EE At Loading - Blended	22%	78%			22%	78%		
Importer after Test	21%	79%			21%	79%		
Decision Variables	Test	Intensity	Test	Intensity	Test	Intensity	Test	Intensity
CE Rec Test	1	5	1	4	1	5	1	5
CE Load Test	1	4	1	5	1	5	1	1
Exp Rec Test	1	5	1	1	1	4	1	5
Blending Portions	80%		20%		81%		19%	
	Blended Testing				Blended Testing			
Exp Load Test	1	5			1	4		
Imp Rec Test*	1	1			1	1		

Nebraska sub-chain, every 4th unit is tested at the country-elevator receiving rather than every 5th shipment. Blending proportions are also adjusted. For this case, 80% of soybeans originate from North Dakota, and 20% originate from Nebraska. This blending combination results in the EAA requirements being met 99.91% of the time, a minimal increase from the base case. The total costs for high-quality soybeans increase from 5.20 c/bu to 6.09 c/bu. The total North Dakota costs increase to .62 c/bu, and Nebraska soybeans increase to 8.32 c/bu. Overall risks increase for both the buyer and seller. The buyer's risk increases to .59%, and the seller's risk increases to 4.51%. Expected disutility increases to 1.0051. The risk premium also increases from .21 c/bu to .27 c/bu.

When the final sensitivity, increased salvage costs, is run, the optimal testing strategy is affected. Location testing is not adjusted, but the intensities change. For the North Dakota sub-chain, testing at export receiving increases to every 4th unit. In the Nebraska sub-chain, only the country-elevator loading test is adjusted, and every shipment there is tested. Blending proportions change as well; 81% of the soybeans are shipped from North Dakota, and 19% are shipped from Nebraska, resulting in the EAA requirements being met 99.93% of the time. The total high-quality soybean costs increase to 9.10 c/bu. North Dakota shipment cost increases to .62 c/bu, and Nebraska shipment costs increase to 8.21 c/bu. The buyer's risks increase to .40% and the seller's risks increase to 4.74%. Expected disutility increases to 1.0052, and the risk premium increases to .21 c/bu.

The blending model shows that, for North Dakota shipments, blending with a smaller portion of higher-quality Nebraska soybeans results in a greater likelihood of meeting the EAA requirements and having a greater portion of flows meet the requirements. When the requirements are relaxed, it is a much better option to purchase soybeans from North Dakota

rather than paying a premium for Nebraska soybeans. Blending Nebraska with North Dakota soybeans results in decreased costs and risks, however, grain handlers require a higher risk premium to account for the increased flows of high-quality soybeans. Sensitivities to testing and salvage costs have effects on the testing costs and risks. Increased salvage costs have the greatest effects on overall costs, although the overall risks only increase slightly. Blending varies for all sensitivities, although the probability of meeting the EAA requirements post-blend remains relatively similar at about 99.9%, indicating that blending and testing are effective ways to insure EAA quality.

Strategy Summary

Sellers make testing and blending strategy decisions in order to minimize costs and risks. The sellers are responsive to the buyers' purchasing strategies. The results presented in this chapter outline the different purchasing strategies that buyers may use: buying based on the quality of the protein, oil, or EAAs. The results presented in Table 5.15 show the optimal testing and blending strategies that sellers would select based on the varying costs and risks that arise when meeting the quality requirements, shown in Table 5.14.

The first case provides a starting point to analyze the altering purchaser requirements. Applying any quality testing in the supply chain reduces the amount of risk that buyers and sellers face. Initially, the buyer's risk is 1.48%, and the seller's risk is 15.46%. By implementing tests within the supply chain, grain handlers can decrease their risk to anywhere between 1.86% and 4.41% for sellers and from .15% to .37% for buyers. By implementing the tests, the risk premium also decreases to anywhere between .08 c/bu and .98 c/bu. Differing purchaser procurement strategies result in various likelihoods of the soybeans meeting the quality requirements, which is to be expected. What is interesting is the effects that different

requirements have on the testing strategy. The likelihood that quality requirements are met determines the best strategies for sellers to take when handling their grain. If the quality is more likely to meet the specifications, then the optimal strategy is to test less. The opposite is true if the soybeans are less likely to meet the quality requirements; then, the optimal strategy is to test more often and more intensely.

Summary

The results in this chapter outline the testing for various quality traits and the resulting output. Tables 5.14 and 5.15 show the outcomes for the different cases presented. Examining the results for each case indicates some market factors that grain handlers face when making decisions about testing, blending, and using the best strategies. It is important to understand the grain handlers' motivation for their decisions. Sensitivities conducted across all cases show that handlers' responses are similar in most cases. The largest and most consistent change to handlers' costs and risks occur when salvage costs increase. Adjustments to variables also alter the best-case testing strategies by increasing the testing locations and intensities. Costs increase anywhere from 1.00 c/bu to 2.50 c/bu, except for the final case where costs increase about 4.00 c/bu. A large portion of these costs come directly from the increased salvage costs, but some additional costs arise from the increased testing to avoid higher salvage costs. One interesting result was the impact that this had on the risks faced by buyers and sellers. Because the testing was increased to avoid salvage costs, the buyer and seller's risk diminished, with the seller's risk dropping by a larger amount than the buyer's risk. This relationship suggested that sellers were very responsive to the negative costs that arose from not meeting specific requirements. The blending model also showed that grain handlers were more willing to purchase higher-quality soybeans from Nebraska to ensure that the quality requirements were met when blending.

Table 5.14. Strategy Summary: Costs and Risks

Testing for All EAAs: 4 Requirements	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6		
	No Testing	Protein	Protein and Oil	Single EAA	All EAA	Blending		
Outputs							ND	NE
Costs						CE Receiving Test	0.25	0.12
CE Receiving Test	-	N/A	0.09	N/A	0.08	CE Loading Test	0.06	0.03
CE Loading Test	-	0.03	0.02	N/A	0.02	EE Receiving Test	0.06	0.34
EE Receiving Test	-	0.03	0.02	N/A	0.01	Total Costs Pre-Blend	0.60	0.74
EE Loading Test	-	0.01	0.01	0.03	0.01	Origin Premium	-	7.50
Imp Receiving Test	0.02	0.01	0.01	0.03	0.00	Total HQ Costs - ND/NE	0.60	7.82
Total Export Test	0.02	0.08	0.15	0.06	0.12	HQ Costs Blended	2.45	
Salvage Costs	4.36	0.63	0.43	0.98	0.38	EE Loading Test	0.01	
Total Export Cost	4.42	0.71	0.58	1.04	0.50	Imp Receiving Test	0.03	
Cost of HQ	10.24	2.04	2.04	1.11	3.39	Total Export Test	2.71	
Risks						Salvage Costs	2.50	
Buyer Risk	1.48%	0.26%	0.32%	0.15%	0.37%	Total Export Cost	1.05	
Seller Risk	15.46%	3.17%	3.78%	1.86%	4.41%	Cost of HQ	5.20	
Total Buyer-Seller Risk	16.69%	3.42%	4.09%	2.01%	4.76%	Risks		
EAA Requirements	0.50					Buyer Risk	0.36%	
Disutility & Risk Premium						Seller Risk	4.31%	
Expected Disutility	1.01	1.00	1.00	1.01	1.00	Total Buyer-Seller Risk	4.66%	
Risk Premium	1.87	0.25	0.12	0.98	0.08	Disutility & Risk Premium		
						Expected Disutility	1.0045	
						Risk Premium	0.21	

Table 5.15. Strategy Summary: Optimal Strategies.

Testing for Protein Only	Case 1		Case 2		Case 3		Case 4		Case 5	
	No Testing		Protein		Protein and Oil		Single EAA		All EAA	
Probability of the Flows Meeting the Requirements										
	HQ	LQ	HQ	LQ	HQ	LQ	HQ	LQ	HQ	LQ
Initial Quality Composition	46%	54%	46%	54%	32%	68%	100%	0%	27%	73%
Farm in Bin	46%	54%	46%	54%	32%	68%	100%	0%	27%	73%
CE in Store	50%	50%	50%	50%	32%	68%	100%	0%	27%	73%
CE Loaded on Track	50%	50%	45%	55%	28%	72%	100%	0%	23%	77%
EE in Store	51%	49%	41%	59%	25%	75%	100%	0%	20%	80%
EE After Loading	51%	49%	36%	64%	21%	79%	96%	4%	16%	84%
Importer after Test	43%	57%	35%	65%	20%	80%	94%	6%	15%	85%
Decision Variables	Test	Intensity	Test	Intensity	Test	Intensity	Test	Intensity	Test	Intensity
CE Rec Test	0	N/A	0	N/A	1	1:5	0	N/A	1	1:5
CE Load Test	0	N/A	1	1:5	1	1:5	0	N/A	1	1:5
Exp Rec Test	0	N/A	1	1:5	1	1:5	0	N/A	1	1:5
Exp Load Test	0	N/A	1	1:1	1	1:1	1	1:1	1	1:1
Imp Rec Test*	1	1:1	1	1:1	1	1:1	1	1:1	1	1:1

The most important change that occurs across cases is the change in quality requirements. Even the smallest change with the quality requirements can greatly alter a grain handler's costs, risks, and optimal testing strategies. The cost variation among cases is anywhere from 1.00 c/bu to 2.00 c/bu. The seller's risk oscillates between 1% and 2% while the buyer's risk only changes by .05% to .3%. It is important to note the likelihood of soybeans meeting the requirements for each case. The variable used to determine high or low quality greatly alters the portions of high-quality and low-quality flows. A greater specification from purchasers would eliminate a large amount of uncertainty for grain handlers.

The overall testing costs are very minimal compared to costs of failure and salvage. All presented cases show a drastic decrease in costs and risks compared to a non-testing system. Grain handlers and adopters of a dual-marketing system should be more inclined to test more frequently and consistently when faced with large discounts or rejection from not complying with the requirements. Further, the results show that the requirements' variability creates a good deal of risk for grain handlers. Testing helps to alleviate the risks that grain handlers may face. Above all else, the greatest determinant for the risk that buyers and sellers face results from the quality requirement levels. Soybean markets do not send clear signals about the quality requirements. This ambiguity creates risk uncertainty within markets. As seen with each case presented, changes in both the quality variable examined and each variable requirement result in drastic costs, risks, and optimal testing strategies. Determining the quality requirements is the most crucial aspect for measuring soybean quality and how grain handlers should market their soybean.

CHAPTER 6: CONCLUSION

Introduction

This thesis presented concerns about soybean quality in North Dakota. A model was developed to determine the impacts of additional testing for a soybean supply chain in order to understand the costs and risks associated with testing for Essential Amino Acids (EAA). Results indicated the risks that buyers and sellers face along with the grain handlers' costs. The following section reviews the concepts, model, and results presented. It also addresses the overall implications for both the private and public sectors. Further discussion about the continued study of this issue is also presented.

Problem and Objectives

Concerns about soybean-protein quality have evolved to become issues for producers and merchandisers in the northern Midwest region. Soybean-protein quality in this region is lower than other regions, and producers and merchandisers face issues including discounts, implicit and explicit, as well as rejected shipments and lost market opportunities. The importance of discounts has become more apparent with the recent growth of soybean production in this region, and the more intensifying international and inter-regional competition for this crop. Lower protein values in the Midwest are thought to be a result of spatially differentiated growing conditions. A major contributor to quality defects in North Dakota is the length of the growing season and the amount of light that soybean plants receive. Due to spatial variability with soybean quality, purchasers are inclined to discount or completely reject shipments from geographic regions, such as North Dakota, with lower quality levels. Figure 6.1 indicates the protein qualities and their spatial distributions. It is evident from the patterns that soybeans grown in North Dakota and other

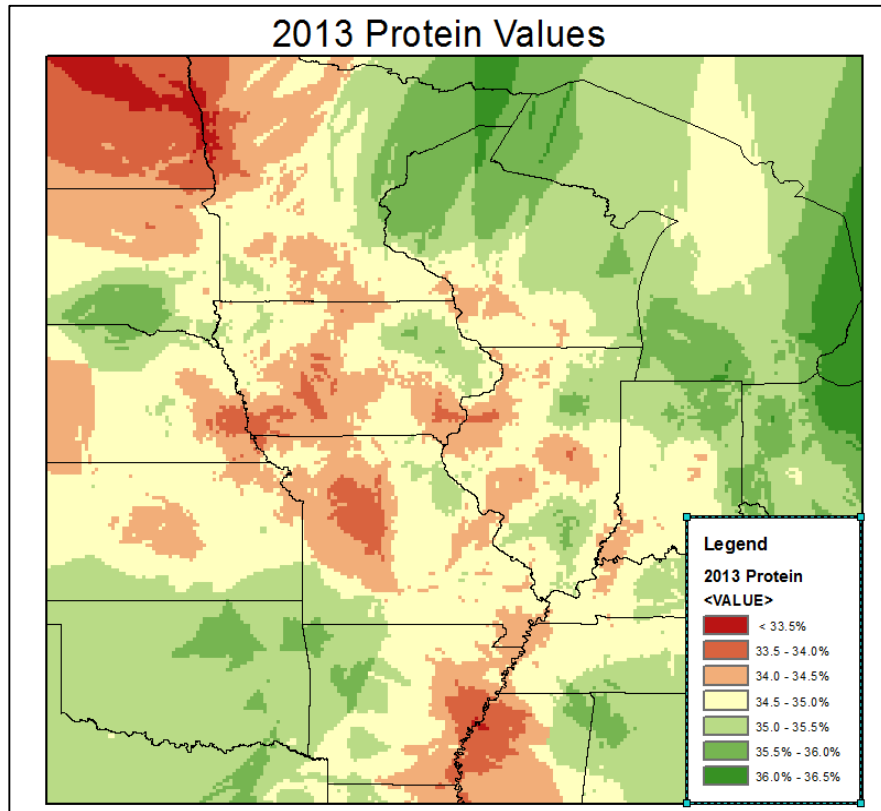


Figure 6.1. Protein Values (USSEC Data 2011-2013).

regions across the same northern plains have lower protein qualities than soybeans from the southern regions.

Traditionally, soybean buyers prefer higher protein levels. This preference is easily measured in the market system, and implicitly, some buyers pay premiums for soybeans that meeting the requirements. Beans that do not meet this specification may not receive this premium, or they may be subject to discounts. North Dakota producers who grow higher-protein soybeans may see increased revenues of \$7.70 to \$12.96 per acre of soybeans grown (United Soybean Board, 2015). There may be negative outcomes for not meeting specific protein requirements. Some buyers refuse to allow shipments from the Pacific Northwest (PNW), presumably for this reason. Rejection of PNW exports creates a problem for growers in the northern Midwest where a large portion of production is shipped to the PNW. Furthermore,

rejection puts growers in this region at a disadvantage when competing with regions where the protein values are higher.

However, protein measurements do not tell the entire story regarding soybean quality. Soybeans are typically measured by the crude protein (CP) content which is determined by the amount of nitrogen content within the soy meal. End users desire higher protein levels due to the nutritional values when used as soybean meal for feed. When soybeans are purchased for protein, they are generally used for crushing and, eventually, utilized as soybean-meal feed for livestock. Sophistication with livestock production has been aided by feeding formulations where livestock producers aim to maximize growth based on feed inputs. However, feeding formulations are not based on the protein values. Rather, the formulations aim to maximize the nutritional value based on the proteins' amino acids. There are over 18 different amino acids found in proteins, however, there are only a handful of amino acids that are essential to aid livestock growth. The five amino acids identified as essential for feeding formulations are cysteine, lysine, methionine, threonine, and tryptophan. These amino acids are known as the Essential Amino Acids (EAA). The problem is that the marketing system readily measures protein levels but not the EAA elements. Using EAAs to measure soybean quality, rather than crude protein, may lead to a better evaluation of soybean values. Using EAA measurements is important for soybeans grown in North Dakota, where protein values are lower than other geographical regions. Table 6.1 shows the summary of the quality variables.

The overall objective of this study is to understand the impacts of the quality requirements within the soybean marketing chain. Specific objectives include (1) What is the quality composition of spatially differentiated soybeans and the likelihood of meeting the varying quality requirements? (2) What are the optimal testing and blending strategies that grain

Table 6.1. Quality Variable's Summary Statistics

	Protein	Oil 13%	Total EAA	CAAV	Lysine	Threonine	Tryptophan	Methionine	Cysteine
North Dakota									
Mean	34.01%	18.20%	5.64	16.62%	2.56	1.53	0.46	0.55	0.54
Standard Deviation	1.97%	1.41%	0.22	0.79%	0.15	0.08	0.04	0.02	0.04
Minimum	29.51%	14.30%	5.08	14.48%	2.17	1.35	0.37	0.49	0.38
Maximum	40.29%	21.31%	6.17	19.20%	2.86	1.77	0.56	0.61	0.64
Nebraska									
Mean	34.60%	18.32%	5.71	16.52%	2.59	1.54	0.47	0.56	0.55
Standard Deviation	1.52%	1.39%	0.19	0.67%	0.13	0.08	0.03	0.03	0.04
Minimum	28.68%	13.42%	5.08	14.61%	2.24	1.35	0.39	0.49	0.39
Maximum	40.27%	21.62%	6.28	19.93%	2.91	1.77	0.57	0.63	0.65
All States									
Mean	34.63%	18.51%	5.71	16.50%	2.58	1.55	0.47	0.56	0.54
Standard Deviation	1.74%	1.38%	0.19	0.66%	0.14	0.09	0.04	0.03	0.04
Minimum	28.59%	11.26%	4.97	13.50%	2.08	1.32	0.30	0.46	0.36
Maximum	42.62%	24.02%	6.50	19.93%	3.01	1.92	0.61	0.80	0.87

handlers should choose given the varying purchaser requirements and preferences? and (3) What costs and risks arise due to a segregated marketing chain?

Crude protein continues to measure the soybean quality's value in the marketplace. EAAs may offer an alternative for evaluating the soybean value. The aim of this study was to determine soybean quality as well as the optimal testing and blending strategies that handlers may use to minimize the costs and risks. Analyzing the soybeans' quality characteristics allowed for a greater understanding of the soybeans' inherent value. It was also important to understand the additional costs and risks that may arise due to extra requirements, testing, and operational procedures that may be required to determine and ensure soybeans' quality. This study analyzed the additional costs and risks that grain handlers may face by taking part in a dual-marketing chain that tests and segregates soybeans based on different quality requirements. Analysis included testing for protein, oil, and EAA. Purchasers may set the requirements based on different quality measures, and the first portion of this study determined the impacts of testing.

The second portion helped to answer the question about optimal blending qualities. Blending two different lots with varying quality offered an additional alternative for ensuring quality and limiting the variability and risks associated with quality uncertainty. Determining the impacts of blending to meet purchasers' requirements was also a focus of the study. With multiple purchasing strategies available for a wide range of end-user preferences, meeting the quality standards was costly and risky for grain handlers and producers. Analyzing these costs and risks was crucial for decision makers to operate efficiently. The study's methods and modeling measured the impacts to grain handling and gave grain handlers optimal strategies to handle soybeans with varying quality.

Methodology and Model

Meeting quality standards for a wide variety of purchasing strategies and preferences left grain handlers with a great deal of uncertainty and risk. There were several strategies and mechanisms that grain handlers might use to mitigate these risks. The study proposed a dual-marketing system that tests, segregates, and blends soybeans to minimize the risk from quality uncertainty, adventitious comingling, and testing errors within the grain-marketing supply chain. When faced with quality uncertainty, grain handlers sought to choose an optimal strategy that minimized the costs and risks of testing and blending.

Chapter 3 presented the theory of expected disutility and the resulting implications for the individual's decisions and optimal responses. Expected utility allows individuals to assess risky situations in order to determine which decision is preferential when outcomes are uncertain. Further analysis of this theory stated that, when decision makers evaluate decisions, they may substitute wealth values with monetary values for the utility of wealth (Serrao & Coelho, 2000). Substitution of wealth allowed individuals to make decisions about investment or infrastructure. From this, it was clear that decision makers, when faced with risky situations, were inclined to choose options that maximized utility. Linear programming provided a methodology to determine the maximal utility based on a function of decision variables. The model presented in Chapter 4 did precisely this. In the dual-marketing chain, grain handlers had the option to test or not test at each point: country-elevator receiving and loading, export-elevator receiving and loading, and importer receiving. Further, grain handlers had a decision about how much to test: every unit, every second unit, every third unit, every fourth unit, or every fifth unit.

The utility function that was used in this study to evaluate the expected utility was an expo-power utility function. Structurally, the expo-power utility function allows for different assumptions about decision makers' risk preference. One different aspect of the theoretical

model presented in Chapter 3 and the empirical model used for estimation was substituting the monetary value for the wealth variable. Rather than substituting an income or revenue function, the model used costs. Using costs altered the implications for the expected utility. Rather than seeking to maximize the expected utility, decision makers attempted to minimize the expected disutility as a result of the additional costs. Within the function, wealth became a negative coefficient that represented the additional costs that arose due to the dual-marketing system's testing and rejection costs. Thus, the objective function became an expected disutility minimization.

The dual-market model embedded testing decisions at various points. The model also incorporated additional costs and risks, some being congruent with the testing decision variables. For each point where testing was implemented, additional testing costs were included. Risks were also incorporated into the model to simulate testing errors and adventitious comingling. There were more costs beyond testing that were included in the model, too. The model was structured such that, if the testing requirements were not met at the importer's receiving level, a salvage cost was applied to all soybeans that did not conform to the specified requirements. Table 6.2 shows the requirements used in the model (75-100 kg). An additional model included a blending-decision variable was developed to determine the effects that blending two heterogeneous quality distributions to ensure that the quality requirements were met. Along with a blending decision, additional testing locations were added to simulate the additional supply chain for the second origin, Nebraska. The model determined how much to blend from Nebraska and North Dakota while testing for all locations. For this model, additional constraints were added to ensure that the blending would meet the requirements 95% of the time.

Table 6.2. Quality Requirements (Merck Manuals, 2015).

Protein & Oil Requirements	Preferred	Lower Limit					
Protein	34%	33%					
Oil	18.50%	18%					
Swine EAA Requirements							
Body Weight (kg)	7-5	7-11	11-25	25-50	50-75	75-100	100-135
Lysine	1.7	1.53	1.4	1.12	0.97	0.84	0.71
Methionine	0.49	0.44	0.4	0.32	0.28	0.25	0.21
Threonine	1.05	0.95	0.87	0.72	0.64	0.56	0.49
Tryptophan	0.28	0.25	0.23	0.19	0.17	0.15	0.13
Cysteine	0.47	0.43	0.39	0.33	0.29	0.25	0.22
Methionine + Cysteine	0.96	0.87	0.79	0.65	0.57	0.5	0.43

The base-case model was used to simulate a scenario where purchasers demanded minimum protein requirements and where no testing was implemented in order to analyze the risks that may arise when no actions are taken to ensure quality. Four more cases were run with differing quality requirements that included optimization for testing strategies. Requirements were tested for protein, protein and oil, single EAA variables, and all EAA variables. For cases that tested multiple variables, a joint probability was used to determine the likelihood that all the requirements were met. The joint probability represented the likelihood that all included variables met the requirements for any given random draw. The final case utilized the blending model and only tested for joint probabilities that all EAA requirements were met. Sensitivities were conducted for all cases to measure the impact of changed minimum requirements, increased testing costs, decreased testing accuracies, and increased salvage costs.

Data for the model were collected from a United States Soybean Export Council survey that analyzed over 5,000 soybeans and determined the quality. Variables included protein, oil, and amino acids. Samples were geocoded by zip code for a three-year period that began in 2011 and ended in 2013. While the quality was impacted both spatially and temporally, only spatial

components were analyzed, and all sample years were aggregated to one data set. Utilizing the data provided in conjunction with the @Risk simulation software, best-fit distributions were used to determine the functional distribution of the requirements for different locations. The model utilized the distributions from North Dakota and Nebraska to determine the likelihood that the minimum requirements would be met.

Stochastic optimization was used to estimate random variables and to determine the optimal distribution of pre-determined risk variables that returned random draws over 10,000 iterations. This random testing and blending strategies for all models and iterations run. @Risk functionality provided a simulation, along with the optimization procedure, sought optimal solutions to minimize the mean solution of the objective function. Functions within @Risk also allowed for descriptions of the randomized variables. Using the @RiskMean function, any outputs that are affected by random variables may be analyzed by mean, standard deviation, minimum, maximum, and other descriptive statistics.

Results Overview

Using stochastic optimization, results that gave insight about the problem presented in this study were gathered. The study's goal was to determine the optimal testing strategies that would minimize disutility and would analyze the resulting costs and risks. Table 6.3 shows the overview of the results for cases 1-5. Table 6.4 shows the results for case 6. The first case that was modeled showed the impacts of a system in which the specifications were set by purchasers with no testing conducted to ensure that quality was managed (except at the importer level where testing was used to quantify and analyze the costs and risks). Case 1 analyzed the impacts of

Table 6.3. Testing Based on Purchaser Requirements: Cases 1-5.

Testing Over All Cases	Case 1		Case 2		Case 3		Case 4		Case 5	
	No Testing		Protein Test		Protein and Oil		Single EAA		All EAA	
Outputs										
Costs (c/bu)										
Total Export Test	0.02		0.08		0.15		0.06		0.12	
Salvage Costs	4.36		0.63		0.43		0.98		0.38	
Total Export Cost	4.42		0.71		0.58		1.04		0.5	
Cost of HQ	10.24		2.04		2.04		1.11		3.39	
Risks										
Buyer Risk	1.48%		.26%		.32%		.15%		.37%	
Seller Risk	15.46%		3.17%		3.78%		1.86%		4.41%	
Total Buyer-Seller Risk	16.69%		3.42%		4.09%		2.01%		4.76%	
Disutility & Risk Premium										
Expected Utility	1.013		1.0048		1.0033		1.0095		1.0027	
Risk Premium (c/bu)	1.87		0.25		0.12		0.98		0.08	
Testing Strategy										
	HQ	LQ	HQ	LQ	HQ	LQ	HQ	LQ	HQ	LQ
Likelihood of Meeting Requirements	43%	57%	35%	65%	20%	80%	94%	6%	15%	85%
Decision Variables	Test	Intensity	Test	Intensity	Test	Intensity	Test	Intensity	Test	Intensity
CE Rec Test	N/A	N/A	0	N/A	1	1:5	0	N/A	1	1:5
CE Load Test	N/A	N/A	1	1:5	1	1:5	0	N/A	1	1:5
Exp Rec Test	N/A	N/A	1	1:5	1	1:5	0	N/A	1	1:5
Exp Load Test	N/A	N/A	1	1:1	1	1:1	1	1:1	1	1:1
Imp Rec Test*	1	1:1	1	1:1	1	1:1	1	1:1	1	1:1

Table 6.4 Testing Based on Purchaser Requirements: Case 6.

Case 6			
Blending			
Costs (c/bu)	ND	NE	
Total HQ Costs - ND/NE	0.60	7.82	
HQ Costs Blended	2.45		
Total Export Test	2.71		
Salvage Costs	2.50		
Total Export Cost	1.05		
Cost of HQ	5.20		
Blended	86%	14%	
Buyer Risk	0.36%		
Seller Risk	4.31%		
Total Buyer-Seller Risk	4.66%		
Expected Disutility	1.0045		
Risk Premium (c/bu)	0.21		
ND		NE	
	HQ	LQ	
	20%	80%	
Test	Intensity	Test	Intensity
	1	1	1:5
	1	1	1:5
	1	1	1:1
	1		
	1		

purchasing requirements of protein at 34%. Without testing, the risks were high for both buyers and sellers. The buyers' risk was measured at 1.48%, meaning that, 1.48% of the time, buyers received a shipment that tested as high quality but was actually low quality. Seller risk was 15.46%, meaning that, 15.46% of the time, sellers would sell a high-quality shipment, but it was rejected because the testing indicated that it was low quality. Total cost of high quality soybeans was reported at 10.24 c/bu due to the high salvage costs.

Because testing was only applied at the importer level, the cost was only .02 c/bu. The output resulted in a risk premium of 1.87 c/bu. The risk premium was the additional cost for which handlers needed to be indifferent in order to market soybeans in a single-marketing system, where low-quality and high-quality soybeans were not differentiated. The percentage of flows that met the importer's requirements was 43%. Using this case as a starting point, the following bullets illustrate the impacts of testing and blending.

- Implementing testing strategies lowered the buyer and seller's risks. Cases 2 through 6 implemented optimal testing-strategy searches. The impacts of testing greatly lowered the risks that buyers and sellers faced. Buyer risk decreased to a range of .15% to .37%, and seller risk decreased to a range of 1.86% to 4.41%.
- Optimal testing strategies varied and were impacted by requirements that the purchasers imposed as well as the likelihood that soybeans met these requirements. If soybean shipments were more likely to meet the minimum quality requirements, testing strategies were loosened, and less testing resulted in a lower disutility. Conversely, if the shipments were less likely to meet requirements, more testing was required to optimize disutility.
- Costs varied depending on the testing strategies and the likelihood of shipments meeting the specified quality requirements. Naturally, the more frequent and intense the testing

was, the greater testing costs were. The total amount of high-quality soybeans in the marketing chain also affected the costs. If there were more bushels to spread out the costs, the costs applied to each bushel of soybeans were lower.

- Risk premiums were dependent on different risk factors and the likelihood of meeting specific purchaser requirements. If risks were higher, grain handlers must be compensated for the additional likelihood of rejection. Likewise, if a greater portion of soybeans were in high-quality flows, a larger portion of assets were at risk. This resulted in an increased risk premium.
- Blending increased the likelihood that flows met the requirements but added additional costs. Blending a portion (13%) of soybeans from Nebraska increased the likelihood that soybeans met the requirements by about 5%, however, costs also increased by about 1.81 c/bu. Buyer and seller risks were lowered, but only minimally. The risk premium also increased by .13 c/bu, but the change was due to reasons mentioned earlier.
- Relaxing requirement constraints had large impacts on all outputs, including optimal testing strategies, costs, buyer and seller risks, and risk premium.
- Increased salvage costs greatly impacted the optimal testing strategies. Grain handlers were very responsive to increased costs from not meeting the requirements and the increased testing. Because of this response, costs and risk premiums increased. Because of increased testing, buyer and seller risks decreased.

Implications of the Study and Opportunities for Further Studies

Changing global commodity markets require that sellers be more aware of the international purchasers' and end users' quality requirements. Currently, the market only determines quality based on protein and oil content. Recent research and literature about soybean

quality suggest that valuing soybeans may go beyond the crude-protein quality that is traditionally used. Measuring EAA quality in soybeans could lead to a better understanding and valuation of soybeans. This thesis presented a model that analyzed soybean quality as well as the optimal testing, segregating, and blending. Costs and risks were analyzed to determine how different purchasing requirements affected the grain handlers' decisions. The model and results presented in this study had several implications for the marketplace and individual grain handlers.

The first implication of this study was that a dual-marketing system that tests, segregates, and/or blends soybeans to meet the quality requirements was feasible at a very low cost. While not all risks can be mitigated, buyers' quality assurance can be given at levels of 1%. Second, the costs of additional testing, blending, and additional risk premiums were relatively low compared to the salvage costs and discounts that sellers may face. This result would imply that system testing and blending could be a viable way to increase soybean quality and to mitigate risk. Third, optimal testing strategies were sensitive to several different factors, including the likelihood of meeting requirements, salvage costs for not conforming to the quality requirements, and different costs and risks that grain handlers face. Of these items, salvage costs and the likelihood of meeting the requirements had the biggest impacts. Fourth, a lack of knowledge about the EAA requirements would create a large risk. As shown in the results, minimal changes to the EAA requirements impacted optimal strategies, costs, risks, and risk premiums. Fifth, the risk premiums suggested that grain handlers would be willing to incorporate segregating, testing, and blending to ensure quality. If buyers were willing to pay the additional premium to assure quality, the grain handlers would be willing to implement a dual-marketing system, such as the one presented. Sixth, premiums and discounts for individual growers or locations may be more

effective to accurately purchase and ensure quality. Specific regions may have quality characteristics that do not agree with the current regional marketplace valuation. Seventh, segregating markets into higher and lower quality versus lower-quality buyers may allow buyers to better communicate with sellers via market signals.

This study analyzed a narrow scope of the impacts of testing soybean quality. EAAs remain a relatively under-researched topic for grain merchandising, and this research has contributed to the thin body of available literature. Further studies about the impacts of valuing EAAs remain possible. Expanding the research could extend to valuing EAAs in a competitive spatial market. Market boundaries exist, preventing sellers from entering certain markets. Valuing the soybean quality based on EAA testing may open markets to new sellers, such as Japan or southeastern Asia, where many purchasers are limited to certain geographic areas. A better understanding of the market requirements for specified buyers would also further the market analysis for soybean-quality traits. The provided data have very geo-specific references, down to zip-code levels. Determining the quality attributes based on specific geographic locations could also lead to further studies about purchaser strategies, where counties may be targeted by buyers who want to ensure superior quality levels. Stochastic dominance, in this case, could provide buyers with both higher-quality soybeans and mitigated risks.

REFERENCES

- Borstein, S. & Kellog, R. (2012). The Incidence of an Oil Glut: Who Benefits from Cheap Crude Oil in the Midwest? *National Bureau of Economic Research*.
- Browbrick, P. (1992). *The Economics of Quality, Grades, and Brands*. London, Routledge.
- Bullock, D.S & Dewquilbet, M. (2002). The Economics of Non-GMO Segregation and Identity Preservation. *Food Policy*. 27: 81-99.
- Chung, T. (1991, October). Incomplete Contracts, Specific Investments, and Risk Sharing. *The Review of Economic Studies*. 58,5: 1031-1042.
- Gast, D. R. (2014). Critical Amino Acid Value (CAAV): Amino Acid Based Assessment Tool for Soybean Meal. *USB Project 1303. Innovative Soybean Meal Quality Analysis Project*. 1-10
- Goodwin, B. K., Holt, M. T., Onel, G., & Prestemon, J. P. (2011, May). *Copula-Based Nonlinear Models of Spatial Market Linkages*. In 2011 Annual Meeting, July 24-26, 2011, Pittsburgh, Pennsylvania (No. 103715). Agricultural and Applied Economics Association.
- Grindley, H.S. (1917). Nitrogenous Constituents of Feeding Stuffs. *Journal of Animal Science*. 1917:133-141.
- Hill, L.D. (1990). *Grain Grades and Standards: Historical Issues Shaping the Future*. Urbana, IL: University of Illinois Press.
- Jeradechachai, T. (2012). Soybean Quality Characteristics. *Northern Crops Institute*. 2012 Annual Update – Northern Crops Institute.

- Johnson, D. D., Wilson, W. W., & Diersen, M. (2001). Quality Uncertainty, Procurement Strategies, and Grain Merchandising Risk: Vomitoxin in Spring Wheat. *Review of Agricultural Economics*. 23,1: 102-119.
- Killam, A. Personal Communication (2015, March).
- Merck Veterinary Manuals. (2009-2015). *Nutritional Requirements of Pigs*. Retrieved from http://www.merckvetmanual.com/mvm/management_and_nutrition/nutrition_pigs/nutritional_requirements_of_pigs.html
- MacDonald, J. M., Perry, J., Ahearn, M. C., Banker, D., Chambers, W., Dimitri, C., & Southard, L. W. (2004). *Contracts, markets, and prices: Organizing the production and use of agricultural commodities*. USDA-ERS Agricultural Economic Report, (837).
- Naeve, S., Orf, J., & Miller-Garvin, J. (2014). Soy Quality and Critical Amino Acid Values: Protein Refinement for Buyers. Presentation for U.S. Soy Global Trade Exchange 2014. Retrieved from <http://www.grainconference.org/>
- Naeve, S., Orf, J., & Weidenbenner, N. (2013). United States Soybean Quality Annual Report.
- Nicholson, W., & Snyder C. (2008). *Microeconomic Theory: Basic Principles and Extensions* (10th ed). Mason, OH. Thomson/South-Western.
- North Dakota Soybean Grower (2013). Northern states Join Forces to Tell the Real Story of U.S. Soybeans' Protein Quality. *North Dakota Soybean Grower Magazine*
- Palisade. (1998). *Risk Optimizer: Optimization with Simulation for Microsoft Excel*. Corporation, Newfield, NY Palisade
- Porter, L., & Rayner, P. (1992). Quality Costing for Total Quality Management. *International Journal of Production Economics*. 27,1: 69-81.

- Saha, A. (1993). Expo-Power Utility: A “Flexible” Form for Absolute and Relative Risk Aversion. *American Journal of Agricultural Economics*. 45,4: 905-913.
- Serrao, A., & Coelho, L. (2000). The role of area-yield crop insurance in farmers' adjustment against risk in a dryland region of Portugal. In *2000 Annual meeting, July 30-August 2, Tampa, FL* (No. 21841). American Agricultural Economics Association (New Name 2008: Agricultural and Applied Economics Association).
- Skadberg, K. (July, 2013). Intermarket Trading Strategies and Risk. *Department of Agribusiness and Applied Economics, North Dakota State University*.
- Sykuta, M., & Parcell, J. (2003). Contract Structure and Design in Identity-Preserved Soybean Production. *Review of Agricultural Economics*. 25,2: 332-350.
- Thakur, M. & Hurburgh,, C. (2007, June). Quality of US Soybean Meal Compared to the Quality of Soybean Meal from Other Origins. *Journal of the American Oil Chemists’ Society*. 84:835-843.
- United Soybean Board. (2015, January). Higher Quality Characteristics. *Ag Professional*. Retrieved from <http://www.agprofessional.com/news/higher-protein-content-boosts-value-soybean-crop>
- Updaw, N. J., Bullock, J. B., & Nichols, T. E. (1976). Pricing Soybeans on the Basis of Oil and Protein Content. *Southern Journal of Agricultural Economics*,8(02), 129-132.
- USSEC. (2006). U.S. Soy: International Buyers’ Guide. Retrieved from USSEC Website. USSEC.org/resources/buyers-guide/
- USSEC. (2008). How the Global Oilseed and Grain Trade Works. Retrieved from [http://www.soyatech.com/userfiles/file/tradeflow_manual\(1\).pdf](http://www.soyatech.com/userfiles/file/tradeflow_manual(1).pdf)
- USSEC (2013). *Soybean Quality Data 2011-2013*.

- USSEC (2015) *Buyers Guide. Chapter 2: Quality Standards for U.S. Soybeans and Soy Products*. Retrieved from <http://ussec.org/resources/buyers-guide/>
- Williamson, O. E. (1979). Transaction-Cost Economics: The Governance of Contractual Relations. *Journal of Law and Economics*. 22,2: 233-261.
- Wilson, W. W. & Dahl, B. (1999). Quality Uncertainty in International Grain Markets: Analytical and Competitive Issues. *Agricultural and Applied Economics*. 21,1: 209-224.
- Wilson, W. W., & Dahl, B. L. (2002). Costs and risks of testing and segregating GM wheat. *Department of Agribusiness and Applied Economics, Agricultural Experiment Station, North Dakota State University*.
- Wilson, W. W., & Dahl, B. (2008). Procurement Strategies to Improve Quality Consistency in Wheat Shipments. *Journal of Agricultural and Resource Economics*. 33,1: 69-86.
- Wilson, W. W. & Dahl, B. (2009, August). Grain Contracting Strategies to Induce Delivery and Performance in Volatile Markets. *Journal of Agricultural and Applied Economics* 41,2: 363-376.
- Wilson, W. W., Dahl B. & Jabs, E. (2006). Optimal Supplier Testing and Tolerance Strategies for Genetically Modified (GM) Wheat. *Agricultural Economics*. 36: 39-48.
- Wilson, W. W., Dahl, B., & Johnson, D.D. (2007). Quality Uncertainty and Challenges to Wheat Procurement. *Canadian Journal of Agricultural Economics*. 55: 315-326.
- Wilson, W. W., Jabs, E. J., & Dahl, B. L. (2003). Optimal Testing Strategies for Genetically Modified Wheat. *Department of Agribusiness and Applied Economics, Agricultural Experiment Station, North Dakota State University*.
- Wilson, W. W., Henry, X., & Dahl, B. L. (2008). Costs and risks of conforming to EU traceability requirements: the case of hard red spring wheat. *Agribusiness*, 24(1), 85.

Winston, W. L. (2001) *Simulating Modeling Using @Risk* (4th Edition). Pacific Grove, CA.
Duxbury.