MARGIN-AT-RISK FOR AGRICULTURAL PROCESSORS:

FLOUR MILLING SCENARIOS

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Margin-at-Risk for Agricultural Processors: Flour Milling Scenarios

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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

ABSTRACT

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Historic market volatility has made risk management decisions by firms in the agricultural supply chain more challenging. Market risk measurement methods, such as Value-at-Risk, were developed in the financial industry to objectively measure, and thus better comprehend, market risk's effect on positions. This thesis gives a thorough background of the issues involved with risk measurement. Different scenarios were then used to demonstrate how the risk measurement method can be applied to the agricultural processing margin.

In this thesis, the flour milling margin was used to demonstrate how a firm can incorporate sophisticated risk analytics into its risk management decision making process. Multiple scenarios were developed to account for different situations faced by flour millers. Ocean freight, exchange rate risk, futures price risk, basis risk and flour price risk are all included to provide examples of how market risk measurement can be beneficial to industry participants.

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CHAPTER I. PROBLEM STATEMENT

Introduction

Unprecedented market volatility has been an important recent development in commodities. Firms across the agricultural commodity supply chain are exposed to more risk. While this provides an opportunity for merchandising and trading firms to profit, processors of agricultural commodities face rising costs of inputs to their respective production process. As a result, controlling price risk exposure is a serious problem facing agricultural processors, as well as all other agricultural market participants, in an environment of historic price volatility.

Hedging price risk exposures has been standard industry practice for many decades but increased volatility has made risk management decisions more complicated. During the volatile markets of 2008, the North Dakota Mill and Elevator reported a $12 million loss during July, August and September (Wetzel, 2008). Volatile cash and futures prices for hard red spring wheat were attributed as the main causes of the losses. In another agricultural processing industry, VeraSun Energy Corp., the United States' second largest ethanol producer, filed for bankruptcy in November 2008. The bankruptcy was attributed to the firm's corn procurement and hedging strategy, along with unfavorable production margins (Hannon, 2008). ConAgra Foods Inc. reported a $33 million hedging loss in the first fiscal quarter of 2008-2009. The losses were primarily a result of decreases in commodity prices in which the prices were already established due to futures hedging (Jargon, 2008). Also in the food industry, General Mills Inc. earnings were cut 17 cents a share due to mark-to-market valuations of commodity hedge positions (General Mills Net Falls 3.6% as Commodity Hedges Drop, 2008). The total hedging losses for General Mills Inc. were reported to be $111 million (Wetzel, 2008). Losses due to hedging were not suffered solely by private end users. The Canadian Wheat Board suffered a net loss of $89.5 million during the fiscal year of 2007-2008 citing its net hedging results as a primary cause (Wheat Board Loses Millions on Bad Futures Trades, 2009). Due to the previous examples and many others, risk management has become an even more important topic in agriculture. According to Will Shropshire, head of agricultural commodities at JPMorgan in London, food companies "are paying more attention to price risk management and putting hedges in place" after the volatile agricultural commodity markets of 2008 (Blas & Farrell, Hedging Helps Foodmakers Through Uncertainty, 2010).

Historically, price risk in agricultural markets has been viewed subjectively and has been mitigated by hedging procedures and the judgment of experienced merchandisers within a firm. Quantitative risk analysis seeks to objectively measure the variance of outcomes. Value at risk (VaR), a portfolio level quantitative risk measurement tool, is one of the common methods of measuring price risk associated with markets. VaR measures the price risk of a firm's individual and aggregative portfolios in dollar terms. It provides a method of measuring probable portfolio losses, facilitating more effective risk management. The importance of VaR is that it provides an objective method of understanding a firm's price risk. Most importantly, it can be used to establish limits of probable price risk. This thesis develops a model and illustrates its potential use for a prototypical agricultural processor, specifically an international processor with import requirements.

Market Volatility

International agricultural processors are exposed to multiple sources of price risk including: (1) commodity prices, (2) exchange rates and (3) freight rates. Commodity prices are the most important source of volatility for agricultural processors. It is important to separate commodity price risk into its two separate but related elements, futures and cash market price risk. Whereas cash markets consist of transactions completed immediately, futures markets are constituted of cleared contractual agreements to buy or sell an asset in the future. The contracts have standardized terms in regard to time, delivery location, quality and quantity; with the only variable being price. Due to differences in time, location and form between the futures contract specifications and the conditions of the numerous cash market transactions, there are discrepancies between the futures price and cash prices. However, these two markets are linked by arbitrage opportunities created by the physical delivery process. This process ensures a relatively high degree of correllation between the two assuming they are not excessively deviating from their theoretical relationship.

In general, the difference between the cash and futures markets, or the basis, is determined by the supply and demand of numerous different geographically disparate cash markets and the cost of transportation between them. The reality of the agricultural supply chain is that there are regions with deficits of supply and surpluses of supply. Thus, the basis is an indication of where grain needs to be efficiently marketed to capitalize upon these discrepancies. The basis describes the relationship between many different geographically disparate cash markets and the global futures market.

Futures markets exist to ensure properly functioning cash markets, as Leuthold states, "Futures markets are extensions of cash markets. They evolved out of existing market forces, and their purpose is to make cash markets work better. They are about the forward pricing of commodities and instruments-a speculative, unavoidable process (Leuthold, Junkus, & Cordier, 1989, p. 4)." Along with the discovery of forward prices, futures markets' other primary function is to provide a mechanism to transfer price risk.

Commodities are inputs to production processes, as a result, production generally would not be stopped because of rising costs of inputs. "To a certain extent I don't really care what I pay for wheat," said George Mason, senior executive, grain buying for Heygates [British flour mill]. "As long as I can maintain my operating margin, I'm happy (Lyddon, 2008)." There are many elements to commodity prices but the most important is the stock/consumption ratio. This is a measure of the ability of supply to meet demand (Atkin, 1995). Recently, the ability of supply to meet demand has been tested in the wheat market. Tables 1 and 2 display recent price volatility in the wheat market. In February 2008, nearby MGEX spring wheat futures contracts traded as high as $25. The primary cause of this was the lowest stock/consumption ratio in history. A secondary cause was a delivery settled futures market anomaly called a "short squeeze". A short squeeze is defined by the CFTC as "a market situation in which lack of supplies tend to force shorts to cover their positions by offsetting at higher prices (CFTC Glossary)." As shown in Figure 1, the anomaly raised the price of wheat into the $20 range, when wheat should have been at $14 or $15 a bushel according to historical stock/consumption levels (What Happened to $22 Wheat?, 2009).

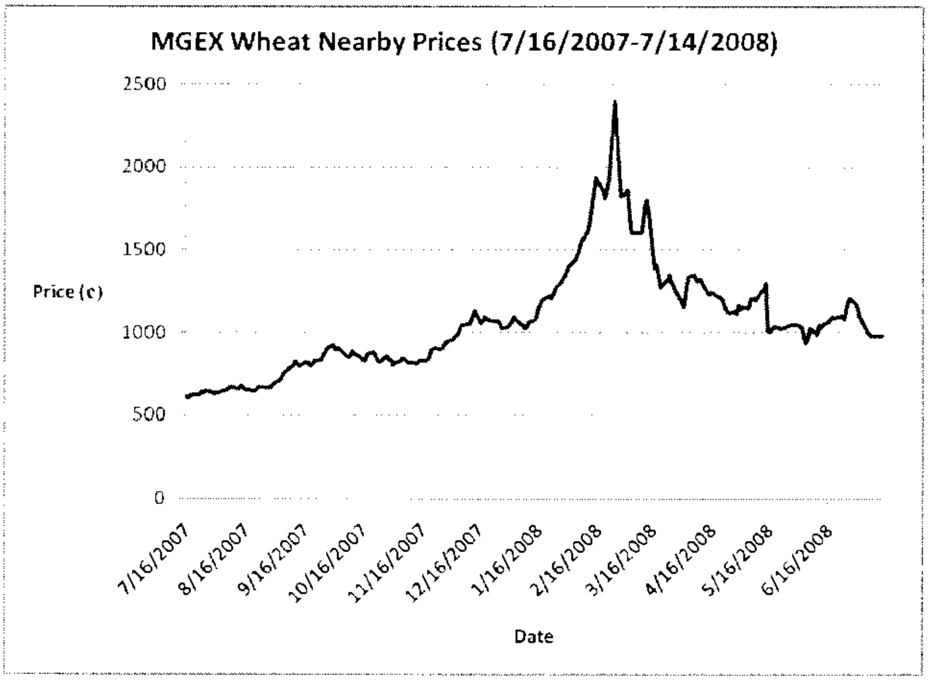

Figure 1 Hard Red Spring Wheat Futures Prices Chart

The year 2010 has been marked by volatility as shown by Figure 2. Drought in the FSU caused supply uncertainty in the wheat market. An example of uncertainty's effect on prices would be the nearby soft red winter wheat contracts on the Chicago Mercantile Exchange, whose prices increased 70% from early June 2008 to early August 2008. Further compounding the uncertainty of supply was the Russian government's decision to ban grain exports (Polansek, 2010). All of these events indicate a tight supply/demand balance in the wheat market, leading to persistent volatility.

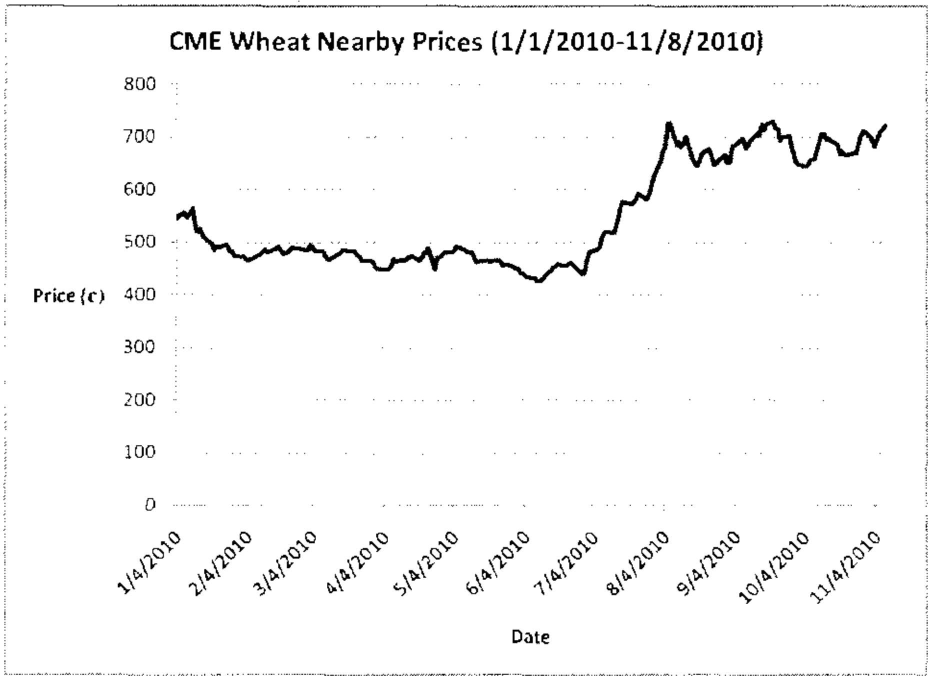

Figure 2 Soft Red Winter Wheat Futures Prices Chart

The UN's Food and Agriculture Organization's Food Outlook report released in November 2010 point to sustained agricultural commodity market volatility. The report warned that farmers must substantially expand production in order to meet expected demand and replenish world grain reserves. The FAO's forecasted bill for global food imports in 2010 was $1,026 billion, up almost 15% from 2009 and approaching 2008's bill of $1,031 billion. To put this in perspective, the average bill for global food imports in the 10 years before the 2007-2008 food crisis was less than $500 billion per year. In addition, the FAO's food price index, which tracks export prices, has been trending higher (Blas, 2010). This trend has led to a record index level of 214.7 in December 2010 (MacDonald, 2011).

In the early 1970's, the Bretton Woods exchange rate system collapsed due primarily to highly diverse rates of inflation among nations (Thomas, 2006). The adjustable-peg (Bretton Woods) system was replaced with a floating exchange rate system. Due to the new system, an active exchange rate forward market emerged and currency futures were introduced on the Chicago Mercantile Exchange in 1972 (Holton, 2002). These new hedging instruments gave international agricultural processors the means to mitigate their exposure to fluctuations in exchange rates.

An important part of the agricultural commodity supply chain is the freight market. Currently, the United States, the European Union, Canada, Australia and Argentina account for approximately 75% of wheat traded internationally (Gwirtz, 2008). The cost of transportation from areas of supply to areas of deficit is the primary cause of spatial price differentials in commodities. Adding further complexity, the freight market is not closely correlated to the price of commodities because its rates are determined by its own unique supply/demand balance (Atkin, 1995). Figure 3 displays recent ocean freight volatility.

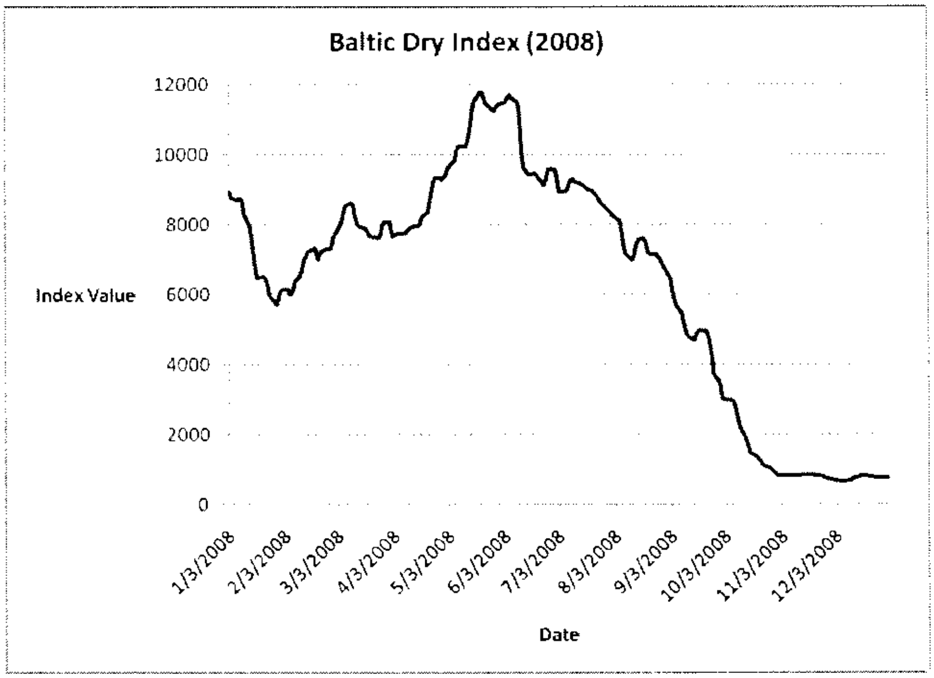

Figure 3 Baltic Dry Index Values

The Baltic Exchange Dry Index hit a record high in May 2008 fueled by China's demand for raw materials, a growing world economy, port congestion and the emergence of new long-haul supply routes. This peak was followed by a nine-year low in early November 2008 as the freight market collapsed during the global economic downturn and the index lost 90% of its value (King, 2008).

Evolution of Risk Measurement

Centuries of progress in the fields of statistics and probability led to Harry Markowitz's seminal paper, Portfolio Selection (Markowitz, 1952). The paper emphasized the benefits of diversification in portfolio analysis. By utilizing mathematical concepts such as variance, covariance and expected return, a portfolio's exposure to price risk could be quantified through the mean-variance framework. The breakthrough of the mean-variance framework initiated the growth and development of market risk measurement.

The proliferation of financial derivatives provided the impetus for the development of risk measurement. The notional amount of derivatives contracts turned over daily grew from insignificant amounts in the early 1970's to a staggering $2.8 trillion in April 2001. These instruments have the ability to magnify gains and losses through leverage. Out of this factor, derivatives and their inherent risk warranted new methods to better comprehend possible gains and losses (Dowd, 2002).

The Glass-Steagall Act of 1933 created a legal separation of commercial banking and investment banking, however during the early 1990's, this legal restriction was eroded by Section 20 affiliates. The Section 20 affiliates exemption allowed commercial banks to participate in limited investment banking enterprises. Banking capital regulations at that time were based on risk-adjusted capital requirments but the methodology used did not account for portfolio diversification benefit. For commercial banks engaged in investment banking activities, this lead to a significant disadvantage in terms of possible leverage. This provided the motivation for JP Morgan, a commercial bank with limited investment banking activities which competed against investment banks with less stringent regulatory requirements, to develop a methodology which accounted for portfolio diversification. JP Morgan developed the RiskMetrics® methodology due to these factors and made it publicly available in 1994. Soon, RiskMetrics® became the industry standard for measuring market risk (Allen, Boudoukh, & Saunders, 2004).

Problem Statement

Agricultural market participants are exposed to historic levels of price risk. For these firms, reporting risk in dollar terms and establishing limits to control risk is essential in order to avoid catastrophic losses due to unforeseen market events. However, the above mentioned developments in market risk measurement provide them with a tool to better limit price risk.

Processor Hedging

Agricultural commodities are used in a wide array of production processes. Most notably among these are flour milling, oilseed crushing, wet corn milling, dry corn milling and barley malting. Each of these processes face varying input prices to their respective process. Because agricultural commodities are often produced in an area of surplus and consumed in an area of deficit, processors in locations of deficit need to transport agricultural commodities for their production process. These firms often know their procurement needs ahead of time making the establishment of forward prices and rates necessary. Processors are hedgers meaning they utilize futures contracts to mitigate flat price risk. The hedging mechanism allows firms to diversify their commercial positions thereby establishing effective purchase and sales prices. Giving concern to the market and effective hedging strategies facilitates a processor's goals of profit, income stability or financial returns (Leuthold, Junkus, & Cordier, 1989).

Recently, food companies have increased their use of derivatives to establish forward prices after the volatile agricultural commodity markets of 2007 and 2008. It has been estimated that up to a third of the world's largest food companies have started new hedging programs after rapid increases in the price of their inputs during 2007 and 2008 (Blas & Farrell, 2010). A failure to control the cost of inputs has consequences and highlights the necessity of effective hedging strategies. Sara Lee Corp. saw its North American Fresh Bakery division suffer an operating loss of $1 million in the first fiscal quarter of 2010-2011. The loss was attributed to higher input costs. Soon after the end of the first fiscal quarter of 2010, Sara Lee Corp. sold its North American Fresh Bakery division to focus on its other higher-margin business divisions (Higher Commodity Costs Drag Down Sara Lee Net, 2010). The use of risk measurement techniques facilitates the reporting of probable portfolio losses to a firm's management. Also, these techniques can be used to establish risk limits, thereby having a benchmark in which to limit exposures. Risk measurement,along with risk management strategies, can prevent a processor from having unexpected spikes in its input costs, which will result in increased output prices and financial losses.

Objectives

The primary objective of this thesis is to develop a risk model that measures the market risk of a prototypical international agricultural processor with import requirements. VaR has been typically utilized for portfolio analysis for trading firms. In the case of agricultural processors, an analysis of the processing margin is more appropriate. Thus, Margin at Risk (MaR), a quantitative risk measure of the processing margin, is a better technique given the unique nature of processing. Specifically, this thesis (1) develops a MaR model that incorporates risk due to exchange rates, freight rates, futures price and basis (2) utilize a MaR computation method and estimation methods which are most appropriate given the situation of the specified agricultural processor, (3) apply the model to different representative case studies of agricultural processors, (4) use MaR as a benchmark to determine probable downside operating margin losses, (5) use MaR to determine which risk management strategies mitigate margina variance and (6) discuss the potential applications of MaR for agricultural processors. The goal of this research is to demonstrate how a quantitative risk measurement methodology can measure a prototypical international agricultural processor's exposure to market risk. The research presents how a representative firm can utilize a quantitative measure to mitigate price risk by selecting the most effective hedging and purchasing strategy and to report probable price risk in dollar terms to management.

Methodology

The most common approach of measuring market risk is utilizing a probabilistic model. VaR is the most common method of probabilistic risk measurement. "Value at risk is a single, summary, statistical measure of possible portfolio losses. Specifically, value at risk is a measure of losses due to "normal" market movements. Losses greater than the value at risk are suffered only with a specified small probability. Subject to the simplifying assumptions used in its calculations, value at risk aggregates all of the risks in a portfolio into a single number suitable for use in the boardroom, reporting to regulators, or disclosure in an annual report (Linsmeier & Pearson, 1996)." Simply put, the VaR measure is the highest possible loss over a certain time period at a specified confidence level (Rachev, Menn, & Fabozzi, 2005).

This thesis develops a MaR model applicable to agricultural processors, both domestic and international. These prototypical processors are defined by their representative institutional situations, both in domestic and international environments. These institutional situations are constructed giving heed to varying levels of government intervention which are derived from realistic public policy.

Organization

This thesis's second chapter contains a background of risk management and measurement as well as recent developments in these two fields. The second chapter also contains previous studies in risk measurement. Chapter three provides a thorough discussion of the technical and managerial issues of risk measurement. Chapter four develops the model and outlines the empirical procedures. Chapter five provides the results of the study while chapter six provides a brief conclusion.

CHAPTER II. BACKGROUND AND PREVIOUS STUDIES

Introduction

Futures markets and other risk management instruments have been developed out of necessity because of uncertainty. A processor with procurement quantity commitments often uses offsetting futures position to financially hedge their cash positions thereby transferring price risk. Without price uncertainty, futures markets' two primary economic functions, risk transference and price discovery, would serve no purpose (Carlton, 1984). Price uncertainty in agriculture is caused by the nature of agricultural production and consumption. This uncertainty provides the motivation for processors to utilize risk management instruments and risk measurement techniques.

Risk is defined by Philippe Jorion (2007, p. 76) as the deviation of uncertain outcomes. Thus, the objective of market risk analysis is to measure the deviation, or volatility, of an uncertain market variable from its expected value. In this manner, potential variation of prices or rates can be probabilistically estimated thereby reducing but not eliminating uncertainty. The VaR methodology incorporates estimated correlation between market risk variables to account for the benefit of asset diversification along with the market risk variables' probable deviations. The methodology then applies the probable deviations to each respective position in a portfolio and the correlations among them, which enables the measurement of an aggregated portfolio's potential downside loss in dollar terms. Measuring downside loss in dollar terms is a significant reason why VaR has flourished as a method of risk measurement.

This chapter discusses the development and growth of market risk measurement. In this discussion, the motivation for market risk analysis is explained. The limitations of VaR are also discussed along with criticisms of the model from the popular press, the industry and academia. Finally, previous studies of VaR germane to this thesis are described.

Evolution of Risk Measurement

Portfolio Theory

Portfolio theory began with Markowitz's seminal paper, Portfolio Selection (Markowitz, 1952). Prior investment theories complied to the rule that investors maximized the discounted value of future returns, also called the expected return. Markowitz argued that this maxim ignored the fact there are diversified portfolios preferable to non-diversified portfolios. Moreover, diversification was an observable reality in finance and a theory of investment behavior needed to incorporate it into its framework.

The crux of portfolio theory is that expected return is desirable and variance is undesirable. An efficient portfolio should maximize the expected return while minimizing the variance of returns. Two implications of this are that investors act rationally and that they maximize expected return for a given tolerance to variance of returns, or their risk tolerance. Within this mean-variance framework, an investor is able to identify different combinations of expected returns that minimize variance. These combinations generate an efficient frontier of points termed the E-V frontier. In accordance with the mean-variance framework, a rational investor can then identify the proper combination of correlated assets that produces an expected return and variance along the E-V frontier that corresponds to their own risk tolerance (Markowitz, 1952). Markowitz's mean-variance framework was never widely adopted at the time, however, due to the onerous data requirements. The framework required data on expected returns and standard deviations of assets along with the correlations between them (Allen, Boudoukh, & Saunders, 2004).

Soon after Markowitz's paper in 1952, Roy published a similar work called, Safety First and the Holding of Assets (Roy, 1952). Roy's framework was similar to Markowitz's; however, he asserted that an investor seeks to reduce catastrophic risk. He termed this assertion the principle of Safety First. The objective of Roy's framework was to minimize the upper bound of the probability that returns would be greater than a specified disaster event. This method was a progression towards the concept of identifying worst case scenarios, an important feature of the VaR methodology.

Baumol continued further with the concept of catastrophic risk with his paper (Baumol, 1963). Baumol's work rejected standard deviation as an appropriate measure of risk and instead espoused the use of a lower confidence limit at a specified probability. Furthermore, Baumol explained that deviation relative to expected return was overlooked. If a portfolio had a lower expected return with the same standard deviation as a portfolio with a higher expected return, then standard deviation is an ineffective risk measure. Baumol argued that Markowitz's E-V frontier generated an overwhelming number of alternatives while adopting a lower confidence limit made the portfolio selection process more tractable by reducing the number of efficient portfolio combinations. This was an important progression towards the value at risk methodology in that it framed downside loss in terms of confidence limits.

Option Pricing

In 1976, Black published the paper, The Pricing of Commodity Contracts (Black, 1976). This was an extension of his previous work on option pricing of stock options with Robert Merton and Myron Scholes in 1973. Both methodologies provided a quantitative framework for the burgeoning derivatives markets of the 1970's and 1980's. The model provided a technique of pricing options on futures contracts using quantitative parameters. The known parameters include time to expiry, the risk-free interest rate, the price of the underlying futures contract and the strike price. The underlying asset's volatility is an unknown parameter and must be estimated. An important implication of the unknown volatility parameter is that the model could backwardly solve for the implied volatility by inputting the observed option premium set by the market into the pricing model.

The pricing model is important to the value at risk process because it provides "the Greeks." The Greeks are the respective partial derivatives of the price of the underlying futures contract, time to expiry, volatility and the risk-free interest rate with respect to the underlying asset's price. This is important to the risk measurement process because parametric value at risk assumes that the portfolio is a linear combination of exposures. Since the exposure to an option premium is non-linear; the delta, or the partial derivative of the option's premium with respect to the underlying futures contract's price, must be used as a linear approximation.

Significant Events in the Financial Industry

The Glass-Steagall Act of 1933 created a legal separation of commercial and investment banking. This was enacted because many banks took heavy losses on proprietary stock investments during the Great Depression. The losses caused fear among depositors leading to bank runs which caused the widespread failure in the U.S. banking industry. The act instituted deposit insurance for commercial banks. To provide integrity to the banking industry, the business of taking deposits and lending was separated from investment banking activities, specifically the underwriting and dealing of securities (Holton, 2002).

Prior to the 1970's, futures markets were solely used in the agricultural industry. However, in August 1971, President Richard Nixon ended the U.S. dollar convertibility to gold. This effectively led to the breakdown of the Bretton Woods exchange rate system. The floating exchange rate system that arose exposed corporations to exchange rate volatility. This led the Chicago Mercantile Exchange to create the International Monetary Market in May 1972. The IMM initially launched seven currency futures contracts (Melamed). Expansion of the futures and options industry into finance continued with the creation of equity options, interest rate futures contracts, treasury-bill futures contracts, treasury-bond futures contracts, commercial paper futures contracts and stock index futures contracts (Chance D. M., 1995).

The entrance of exotic derivatives occurred in the 1980's. An exotic derivative differs from exchange traded futures and options in that they do not have standard well-defined properties and are not traded actively. Exotic derivatives are over-the-counter non-standard financial products created by financial engineers (Hull, 2008). During this time, large corporations were starting to frequently use derivatives to hedge and speculate on a wide variety of risks. As market risk was becoming more of an issue, financial engineers created increasingly complex financial instruments to mitigate or exploit market volatility. As the use of these complex derivatives grew, the financial industry became increasingly leveraged (Chance, A Brief History of Derivatives, 1998). As of June 2007, the over-the-counter derivatives market had grown to notional value of $516.4 trillion and the exchange traded market had grown to a notional value of $96.7 trillion (Hull, 2008).

The Basel Accord of 1988 was a monumental agreement for the regulation of commercial banks. The accord created a minimum standard for capital requirements for credit risks and to standardize the global regulatory framework thereby creating a competitive atmosphere. The objective was to strengthen the integrity of the international banking system by ensuring banks maintained a buffer against potential losses (Jorion, 2007).

The Glass-Steagall Act of 1933 did not provide the legislative framework for the changes in the financial industry, limiting its regulatory effectiveness. Large commercial banks began to have large overseas securities operations by the mid 1980's. The same banks were also permitted to engage in limited domestic operations through Section 20 subsidiaries, who were not forbidden to engage in domestics securities activities. Also, the Glass-Steagall Act did not anticipate the growth of the currency futures market and the over-the-counter derivatives markets. Due to this, large commercial banks in the United States were taking significant market risks in investment banking activities by the early 1990's. These activities included foreign exchange, financial futures and over-the-counter derivatives (Holton 2002). As banks started to increase their investment banking activity during the 1990's, the original Basel Accord's capital requirement framework of only accounting for credit risk proved ineffective. In 1996, the accord was amended to require a capital charge for market risks (Jorion, 2007).

The 1990's were also marred by a series of derivatives blowups. In 1993, German metal production and trading company, Metallgesellschaft, took large positions whose profitability depended on an inverted futures market. As the market switched to a carry structure, the company soon began losing large amounts of money on their leveraged positions. The estimated losses of the Metallgesellschaft blowup were DM1.87 billion. The Orange County Investment Pool of Orange County, California took large leveraged positions on the differentials between long-term and short-term interest rates. In 1994, the losses from these positions totaled $1.6 million (Shirreff, 2004). In 1995, a single rogue trader lost Barings PLC $1.3 billion. These losses were the consequence of a large exposure to the Japanese stock market, in the form of stock index futures contracts. The losses from the single trader bankrupted the venerable 233 year-old institution (Jorion, 2007). These served as a cautionary tale of the potentially explosive nature of derivatives. The nature of financial leverage is that gains and losses are magnified. These blowups affirmed the necessity of risk measurement techniques to better understand the probability of catastrophic losses.

Due to the above mentioned circumstances, the need for risk measurement became of vital importance to the financial industry. JP Morgan was a commercial bank involved in investment banking activities. Being a commercial bank with regulatory capital requirements put JP Morgan in an uncompetitive position compared to investment banks. JP Morgan thus had the incentive to create a method of measuring market risk that accounted for correlation, as the capital requirements at the time did not account for diversification (Allen, Boudoukh, & Saunders, 2004). In October 1994, JP Morgan released its internal risk measurement methodology including a technical document and a free data set of volatilities and correlations. The RiskMetrics® methodology soon became the benchmark for risk measurement (Mina & Yi Xiao, 2001).

In June 2004, the Basel Accord II was finalized. The new accord broadened the scope of risks that banks needed to account for. The three pillars of the accord included minimum risk-based capital requirements, supervisory review and market discipline. Capital charges were now based on credit risk, market risk and operational risk. This provided a more holistic framework than the original and amended accord. The other two pillars emphasized increased regulation and reporting (Jorion, 2007).

Estimating Volatility

Volatility is an important component of option pricing models. Also, it is important to the VaR process as it determines the distribution of relative price changes, providing a measure of the level of price variance in a market (Spinner, 1997). It can be specifically defined as the standard deviation of logarithmic returns (Dowd, 2002). Moving average methods and GARCH are common measures of historical volatility. Another variance measure, implied volatility, is not based on historical data but is based on information provided by options markets.

Simple Moving Average

A simplistic method of estimating historical volatility is an equally weighted moving average. Dowd provides the following equation (Dowd, 2002).

$$\sigma^2 = \sum_{i=1}^{n} \frac{x_{t-i}^2}{n}$$

In the above equation, σ^2 is the the volatility estimate, x are logarithmic returns, t is the current time period and n is the number of observations in the sample period.

The primary limitation of the method is that each observation is weighted equally, including observations farther back in time. Because of this, past events have the same impact as recent events on the volatility estimate. As a consequence, a large return occurs at time t and impacts the volatility estimate until n, the end of the sample period. As it moves outside of the sample period, it is dropped and the volatility estimate reduces dramatically. This is referred to as a "ghost effect" and severely limits the effectiveness of the simple moving average method (Dowd, 2002). Also, longer sample periods utilized in the method produce more stable volatility estimates through time due to the weights of each observation being less. Due to this, longer periods provide a more precise estimate but ignore the underlying variation of price changes (Jorion, 2007).

Exponentially Weighted Moving Average

The most common method of estimating volatility in the parametric method is by using an exponentially weighted moving average (EWMA). EWMA is an improved method of estimating volatility over the simple moving average method. In this method, the weighting scheme decreases exponentially back in time through the sample period. Recent market behavior is given more weight which is a more reasonable assumption than an equally weighted scheme. The recursive EWMA formula is presented below (Hull, 2008).

$$\sigma_n^2 = (1-\lambda)\sum_{i=1}^{m} \lambda^{i-1} u_{n-1}^2 + \lambda^m \sigma_{n-m}^2$$

In the formula above, σ^2 is the volatility estimate for day n, λ is the weighting decay parameter, m is the number of observations in the sample period, n is the current time period, u is a logarithmic return.

The formula is defined as recursive because the volatility forecast is based on the previous period's volatility forecast and the most recent innovation. Due to the limited data required to estimate the recursive EWMA, it is the method employed by the RiskMetrics® methodology.

The EWMA method implies that the current estimate of volatility is appropriate for any period in the future's volatility forecast. This flat estimate disregards any recent dynamics in price movements. For example, if volatility has been rising steadily, the EWMA forecasts a future volatility that is the same as the current volatility. Assuming that volatility is flat or constant is a significant drawback of the method (Dowd, 2002).

The previous mentioned drawback is significant because research indicates that volatility is cyclical and varies through time. This phenomenon is called volatility clustering. Defining this concept is as follows, periods of high volatility will persistently be followed by high volatility and vice versa. The EWMA method accounts for this phenomenon by weighting recent market activity more. However, the method's flat forecast hinders the estimation. Estimating volatility with accuracy is important because it affects the distribution of returns. The presence of volatility clustering leads to fat-tailed realized distributions. Failure to account for the probability of extreme events can cause an inaccurate measure of extreme downside risk, the essential characteristic of the value at risk measure (Allen, Boudoukh, & Saunders, 2004).

Another limitation is the selection of the decay parameter. The RiskMetrics® methodology assumes a value of .94 across all assets. This is done for the sake of simplicity. However, it is a poor assumption that all markets react to changes in volatility in the same manner. In some markets, a spike in volatility will be more persistent than other markets (Lawrence, 1995). It is possible to optimize the decay parameter using a mean squared error (MSE) procedure. The procedure measures the deviations between forecasted and realized volatility by taking the squared error between forecasted volatility and realized volatility. The MSE is then minimized over an array of smoothing parameters (Allen, Boudoukh, & Saunders, 2004).

Generalized Autoregressive Conditional Heteroskedasticity

The motivation for GARCH is that time series data are subject to exogenous events that have a considerable impact on them. Often, large positive and large negative observations tend to appear in cluster. Two important concepts are valid to describe this type of clustering, autocorrelation and conditional heteroskedasticity. Autocorrelation is defined as "correlation between members of observations ordered in time (Gujarati & Porter, 2010, p. 313). Conditional heteroskedasticity is defined as variance that changes conditionally of time (Brooks, 2002). These are two statistical concepts used to account for the reality of time series data. The autoregressive conditional heteroskedasticity (ARCH) model was first proposed by Engle (1982). The ARCH model progressed towards the generalized version, proposed by Bollerslev (1986). GARCH is more common and considered an improvement because it is more parsimonious and avoids over fitting (Brooks, 2002). Bollerslev, Chou and Kroner (1992) provide a thorough survey of ARCH type models.

The equation for GARCH(1,1), the most common GARCH lag structure, is provided by Hull (Hull, 2008).

$$\sigma_n^2 = \gamma V_L + \alpha u_{n-1}^2 + \beta \sigma_{n-1}^2$$

where V_L is the long run average variance, u^2 is a squared return and σ^2 is the conditional variance. The parameters sum to one such that

$$\gamma + \alpha + \beta = 1$$

By setting $\omega = \gamma V_L$, GARCH(1,1) can be expressed alternatively (Hull, 2008).

$$\sigma_n^2 = \omega + \alpha u_{n-1}^2 + \beta \sigma_{n-1}^2$$

In this form, ω, α and β are estimated first, then γ can be calculated as $1\text{-}\alpha\text{-}\beta$. V_L can then be calculated as ω/γ. To ensure a stable GARCH process, it is required that $\alpha+\beta<1$. If this is not done, the weight of V_L is negative (Hull, 2008). Also, it is important to note that EWMA is a special case of GARCH such that $\gamma=0$, $\alpha=1\text{-}\lambda$ and $\beta=\lambda$ (Hull, 2008).

GARCH has been applied to different problems in the field of agri-business. GARCH has been utilized numerous times to the problem of optimal hedge ratios in agriculture. Myers (1991); Baillie and Myers (1991); Moschini and Arahyula (1993); Garcia, Roh and Leuthold (1995); Bera, Garcia and Roh (1997); Manfredo, Garcia and Leuthold (2000); Moschini and Myers (2001) have applied the GARCH methodology to different circumstances in agricultural hedging requiring a hedge ratio conditional of time. Yang, Koo and Wilson (1992) utilized GARCH to forecast crop yields.

Implied Volatility

The primary criticism of volatility estimates based on historical data is that they react to market events. In dynamic markets that are constantly being influenced by new information, a historical volatility measure does not factor the market's future expectations of price variance. Option markets facilitate the discovery of market volatility through the use of option pricing models. Option premiums are determined by a number of observable factors with the standard deviation of the underlying asset price, or volatility, being unknown. An implied standard deviation, a measure of volatility over the option contract's term to maturity, can be inferred from the market price of an option premium through the use of an option pricing model. Jorion (2007) argues that implied parameters should be used in VaR models whenever possible due to the fact that it is a forward looking variance measure.

Estimating Correlation

Correlation and Copulas

Typically, correlation coefficients are used to measure dependence between variables. An implication of this is that the variables are linearly related. Due to this, the probability of extreme observations is discounted. Research indicates that joint distributions are non-normal invalidating the assumption of joint normality. During the aggregation of the portfolio, the tail behavior of the joint distribution is inaccurately modeled leading to an inaccurate risk measure (Jorion, 2007).

A growing method of measuring dependence is the copula. The copula was first proved in 1959 by Sklar's Theorem. The theorem stated that marginal distributions can be coupled by the use of a copula to construct a multivariate distribution. The copula process can be separated into two parts, the specification of the marginal distributions of the multivariate equation and the specification of the dependence structure of the equation by the usage of the copula function. Jorion (2007) explains that the copula is a function of the marginal distributions, which range from 0 to 1. For a bivariate copula, c_{12}, there are two marginal distributions, $F_1(x_1)$ and $F_2(x_2)$, and parameter θ.

$$c_{12}[F_1(x_1), F_2(x_2); \theta]$$

Sklar's theorem states that a copula exists which links the marginal densities of joint densities, expressed in notation below.

$$f_{12}(x_1, x_2) = f_1(x_1) \times f_2(x_2) \times c_{12}[F_1(x_1), F_2(x_2); \theta]$$

Jorion (2007) provides a multivariate normal distribution as an example. The example assumes that all variables have zero mean and unit standard deviation, or are standard normal. In the notation below, Φ is the normal probability density function, N is the cumulative normal function, c^N is the normal copula and ρ is the correlation coefficient.

$$f_1(x_1) = \Phi(x_1) \qquad f_2(x_2) = \Phi(x_2)$$

Given your two normal marginal distributions, they can be linked by a normal copula as expressed in the notation below.

$$f_{12}(x_1, x_2) = \Phi(x_1, x_2; \rho) = \Phi(x_1) \times \Phi(x_2) \times c_{12}^N[N(x_1), N(x_2); \rho]$$

By linking the marginal distributions with the copula, different functional forms can be used for the marginal distributions and the copula (Jorion, 2007). The advantage of this approach is that a non-linear dependence structure can be modeled. As a result of modeling non-linear dependence, extreme events can be modeled as a result of accounting for non-linear joint relationships (Rachev, Menn, & Fabozzi, 2005).

Criticism of Value at Risk

Academic and Industry Criticisms

The VaR methodology has been criticized for a number of reasons. Most notably are the following: risk measurement is conceptually flawed, different methods of implementing value at risk lead to different measures, traders possibly gaming their risk measure, the methodology potentially de-stabilizing the economy, the methodology is a non-coherent risk measure and the issue of time aggregation.

The most vociferous critic of VaR's conceptual flaws has been Nassim Taleb. His criticism stems from the belief that placing too much emphasize on statistical analysis is dangerous. He states, "Measuring events that are unmeasurable can sometimes make things worse. A measuring process that lowers your anxiety level can mislead you into a false sense of security (Taleb, 1998)." An important implication of this criticism is the instability of the input parameters, volatility and correlation. He has also criticized the application of principles of the physical sciences in the fields of the social sciences. To quote Taleb, "I hold that, in economics and the social sciences, engineering has been the science of misplaced and misdirected concreteness (Taleb & Jorion, The Jorion-Taleb Debate, 1997)." Another critic of the value at risk concept is Richard Hoppe. He criticized the use of statistical methods without understanding the implications of the assumptions made for mathematical tractability. To quote Hoppe, "Given a distribution of returns that is non-normal, especially at the extremes, and probably also non-stationary and/or serially dependent, the seeming exactness and "scientific" appearance of variance-based estimates of risk misrepresent the real situation. The alleged precision is far beyond what is possible (Hoppe, 1998)."

Others have criticized the fact that implementing different risk measurement methodologies result in different measures. "[the] VaR changes significantly based on the time horizon, data base, correlation assumptions, mathematical models, and quantitative techniques that are used. Accordingly, VaR does not provide certainty or confidence of outcomes, but rather an expectation of outcomes based on a specific set of assumptions (Beder, 1995)." Beder emphasized the importance of model risk, the variance of risk measures caused by the different models available. Beder argues further that many risk variables are incapable of being measured quantitatively, thus diminishing a risk measurement method's effectiveness. Marshal and Siegel emphasized the importance of systems risk, the variance caused by the different applications of the same model (Marshall & Siegel, 1996). Their research consisted of requesting different software vendors, all who used the RiskMetrics® methodology, to provide risk measures from the same data. They found a great degree of variance between implementations of the same model. Also, the variation was related to the complexity of the asset. This indicates that the results rely on the detailed assumptions of each firm's model and the professionals who operate the modeling process.

It is also possible for traders to game the VaR system. This involves engaging in risky trades that result in a low measurement of risk. An example of this is if traders purposefully enter into markets that have exhibited little volatility for the sole reason of producing a low VaR measure. The recent market environment, however, will not account for potential volatile environments. Another example of this is using an at-the-money short straddle option strategy whose delta will be close to zero. If the VaR method employed doesn't account for gamma risk then the risk measure does not capture the total risk (Jorion, 2007). Figure 4 is the payoff diagram of an at-the-money short strangle option strategy. As the price of the underlying futures changes, the curvature of the option's value, or gamma, negatively impacts the value of this strategy.

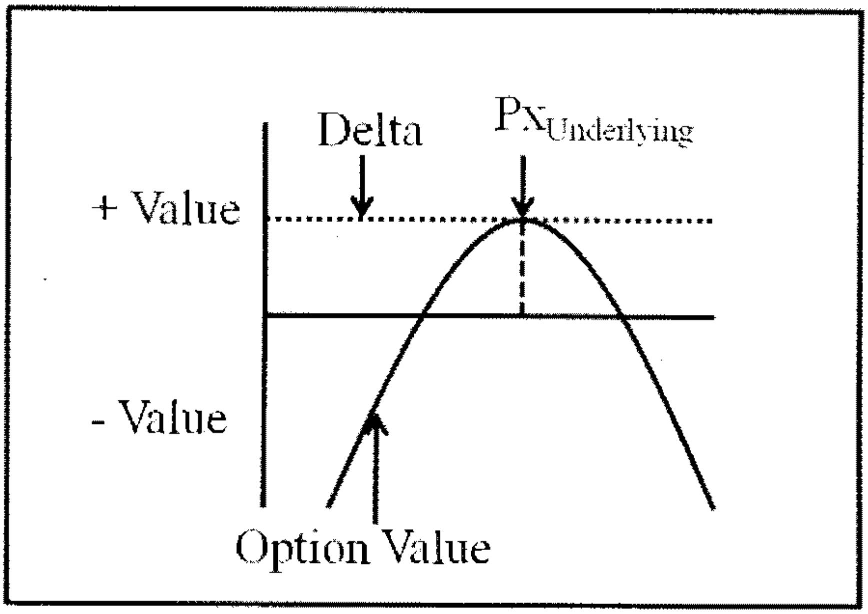

Figure 4 Payoff Diagram of an At-The-Money Short Strangle Strategy

Danielsson criticizes the properties of VaR, explaining that the risk model becomes ineffective during times of crisis because the stochastic process of market risk variables is endogenous to the behavior of market participants. Suggesting that if the risk process becomes the target of risk control, it changes the dynamics of the market; making the forecasting of market risk unreliable (Danielsson, 2000). A result of this would be risk limits giving managers an incentive to protect themselves against probable minor losses while exposing themselves to improbable major losses. If the risk measurement method is prevalent in the industry, the financial system could become de-stabilized because of risk modeling's perverse incentives (Dowd, 2002).

Finally, VaR has also been criticized from a more technical perspective, specifically that the method is not a coherent risk measure. The reason it is not a coherent risk measure is because it does not satisfy the property of sub-additivity. Sub-additivity can be defined by the phrase "a merger does not create extra risk (Artzner, Delbaen, Eber, & Heath, 1999)." Applying this definition to the value at risk framework, the VaR method could result in a situation where the risk of the sum of individual exposures is greater than the sum of the individual exposures.

Value at Risk, Market Crashes and the Popular Press

The most notable of derivatives blowups was the case of Long-Term Capital Management. After taking heavy losses during the flight to quality following the Russian default crisis, the Federal Reserve stepped in to mediate a buy-out of the hedge fund(Shirreff, 2004). Following the blowup, there were many articles written in the press about the dangers of derivatives highlighting the dangers of complex derivatives and calling for increased regulation, Barboza and Gerth's (1998) being an example.

During the financial crisis of 2008, the LTCM event was frequently referenced as an indication that the market had not learned from previous crashes. Over-the-counter derivatives and risk models again came under heavy criticism, especially the effectiveness of dependence estimation during market crashes (Lowenstein, 2008).

Three notable articles were written during the recent financial crisis. The first was Salmon's (2009) article published in the periodical, *Wired*. The article focused on the Gaussian copula's use in modeling mortgage default dependence. The major criticism of the article was that the use of tractable mathematical models didn't reflect the underlying reality. A specific criticism was the use of the copula and its ineffectiveness in estimating dependence. Paul Wilmott, a quantitative finance consultant and lecturer, provided this quote for the article, "correlations between financial quantities are notoriously unstable. (Salmon, 2009, p. 5)"

The second article was published in the periodical, *The Economist*. The article mentioned the usefulness of VaR in markets suchs as interest rates and foreign exchange. Where VaR went awry was in debt markets, specifically mortgage debt markets. Complex instruments, such as collateralized debt obligations, were complex to the point of being faulty. The models used to measure the risk of these complex instruments were unable to provide insight into extreme situations. For a firm to understand losses outside of the specified confidence level, it needs to stress portfolios. The failure of accounting for fat-tailed distributions and inadequate stress testing procedures lead to large losses (Number-Crunchers Crunched, 2010).

Third, Nocera's (2009) article published in the *New York Times*. The article gives a description of the development of VaR and quotes different risk practitioners in the financial industry. Focusing on the limitations of VaR-based risk management, Nocera gives an explanation of the events leading to the financial crisis. The use of historical data to predict future events is mentioned, in particular the use of short time frames of historical data for VaR models applied to mortgage investments. As a result of using historical data, VaR under predicted market risk exposure because "normal" market conditions, portfolio changes within the distribution's confidence interval, were estimated from tranquil market environments. The lack of insight into the portfolio distribution's tail behavior was also discussed. Two notable quotes are provided from industry sources concerning VaR's value in providing useful information concerning "non-normal" market conditions, "[VaR] is like an air bag that works all the time, except when you have a car accident (Nocera, p. 2)." Also, "In peacetime, you think about other people's intentions. In wartime, only their capabilities matter. VaR is a peacetime statistic (Nocera, p. 12)." Among other criticisms mentioned are VaR's inability to measure liquidity risk and the failure to account for gamma risk in the measurement process. Nocera also considered the over-reliance of institutions' management on the VaR measure. Nocera states, "[with] risk having been transformed into mathematical conceit, the real meaning of risk had been forgotten. Instead of scrutinizing VaR for signs of impending trouble, they took comfort in a number (Nocera, 2009, p. 15)." David Viniar, Chief Financial Officer for Goldman Sachs, provided this quote for Nocera's article, "VaR is a useful tool. The more liquid the asset, the better the tool. The more history, the better the tool. The less of both, the worse it is. It helps you understand what you should expect to happen on a daily basis in an environment that is roughly the same (Nocera, p. 15)."

On a final note, Till Guldimann, one of the original architects of risk modeling at JP Morgan, observed that "risk measurement and management continues to be as much a craft as it is a science" and "[that] no amount of sophisticated analytics will replace experience and professional judgment in managing risks (Marshall & Siegel, 1996, p. 5) ."

Previous Studies in Agri-Business Risk Management

The VaR concept has been previously utilized in an array of agri-business applications. Manfredo and Leuthold (Value-at-Risk Analysis: A Review and the Potential for Agricultural Applications, 1999) provided a review of agricultural applications of VaR prior to 1999 and a thorough examination of potential future uses of the VaR methodology in agri-business. In their discussion of potential agri-business applications of VaR, they deem that VaR has benefit "in making hedging decisions, managing cash flows, setting position limits, and overall portfolio selection and allocation (Manfredo & Leuthold, 1999, p. 100)." Along with these general potential applications, they identify specific cases in which VaR could benefit. Publicly traded agri-business firms with market risk exposures must comply with SEC regulations. In this context, VaR could be used to quantify market risk exposures for the purpose of reporting to regulators and shareholders. VaR could provide elevators and agricultural producers with a probable measure of downside market risk exposure among forward contracting alternatives, which possibly could have prevented the hedge-to-arrive crisis of 1996. VaR was also identified as having considerable potential for quantifying credit risk exposures for agricultural lenders who are indirectly exposed to market risk through their creditors (Manfredo & Leuthold, 1999).

The VaR concept has been primarily applied to problems of market risk. Manfredo and Leuthold (Measuring Market Risk of the Cattle Feeding Margin: An Application of Value-at-Risk Analysis, 1999) developed different methods of estimating VaR for the cattle feeding margin, using their empirical results to examine the effectiveness of the VaR methods in predicting catastrophic movements. Baker and Gloy (2000) evaluated different methods of evaluating risk management strategies, most notably VaR and the Sharpe ratio, for crop and hog operations.

Odening and Hinrichs (2002) employed Cash Flow at Risk, which is simply the VaR concept being applied to the gross margin, and Extreme Value Theory (EVT) to quantify the market risk of hog production, specifically three different types of hog producers. Sanders and Manfredo (2002) develop a demonstrative example of VaR's usage in the foodservice industry. Manfredo, Richards and McDermott (2003) used the VaR methodology to assess different risk management strategies for grain merchandising cooperatives. Zylstra, Kilmer and Uryasev (2003) eschewed VaR, opting instead for the related Expected Tail Loss (ETL) measure described in chapter three, alternatively known as Conditional Value at Risk (CVaR). ETL is incorporated into an optimal hedge ratio model for dairy producers as a measure of risk with return on equity being a profitability measure. Prichett et al. (2004) examine a representative farm's revenue distribution, using VaR as a measure of downside loss. The research incorporates different sources of revenue including cash market sales, crop insurance indemnities, hedging alternatives and government payments; assessing the effect of each on the revenue distribution and thus the VaR.

Bamba and Maynard (2004) analyze the effectiveness of Class III Milk futures for different geographic regions. The research focused on the effectiveness of uniform hedging strategies across the different geographic regions with the hedge horizon and signal being key elements. Siaplay, Nganje and Kaitibie (2005) analyzed the effectiveness of VaR in predicting losses of firm profitability due to food safety issues. White and Dawson (2005) utilized VaR to quantify price risk exposure for a representative U.K. farm, using both GARCH and the RiskMetrics® methods and comparing the effectiveness of each. This thesis is an extension of Wilson, Nganje and Hawes' (2007) previous work. Where their research explored the use of VaR in bakery procurement, this thesis applies VaR to a prototypical agricultural processor with commodity import requirements and the consequent risk exposures.

Whereas the previously mentioned research used the VaR framework to confront problems associated with market risk, others have used VaR for issues concerning agricultural lending. Katchova and Barry (2003) utilized the VaR concept to develop credit risk models to estimate capital requirements needed to cover loan default losses for agricultural lenders under the New Basel Capital Accord. Zech and Pederson (2004) develop a model to generate the distribution of loan default losses for a representative agricultural lender, enabling a VaR measure to be identified. The credit risk model incorporates sector correlations, accounting for the diversification benefit of holding different types of agricultural creditors in a portfolio. Larsen, Vedenov and Leatham (2009) developed a portfolio optimization model using a copula-based CVaR to identify optimal allocations of dryland wheat production returns among three geographic regions. This research has implications for agri-business firms' diversification efforts, for example, an agricultural lender seeking to build a robust loan portfolio through geographic diversification of credit origination.

Finally, VaR has been applied to problems of insuring agricultural producers. Bamba (2004) used a VaR measure to assess the revenue risk reduction potential of index rainfall insurance contracts for farmers.

CHAPTER III. TECHNICAL AND MANAGERIAL ISSUES

Introduction

The introduction of portfolio theory in the 1950's laid the theoretical underpinnings for future advancements in market risk measurement. Markowitz and Roy's work were the beginnings of the field but Baumol's work (Baumol, 1963) was an important progression in that it framed downside loss in terms of confidence limits. Baumol calculated the lower confidence limit of losses (L) with the following equation, $L = E - K\sigma$. In this equation, E is the expected portfolio return; K is a constant that depends on an investor's risk appetite and σ is the standard deviation of portfolio returns. As evidenced, the beginnings of modern portfolio theory provided the concept for the future development of the VaR methodology.

Conceptually, VaR is a measure in dollar terms of the possible downside loss of a portfolio. Specifically, it is a measure of probable portfolio losses given the assets' volatilities and correlations over a certain time period assuming "normal" market conditions. Losses greater than the measure occur during "non-normal" market conditions and are suffered with a small, specified probability. It allows for a firm's market risks to be aggregated thus providing a measure that accounts for the diversification benefit of a portfolio composed of many different types of assets. The measure is useful as it provides an estimate of probable losses in a single dollar amount, which can be reported to a firm's board of directors, regulators and investors. Figure 5 presents the VaR concept in graphical form.

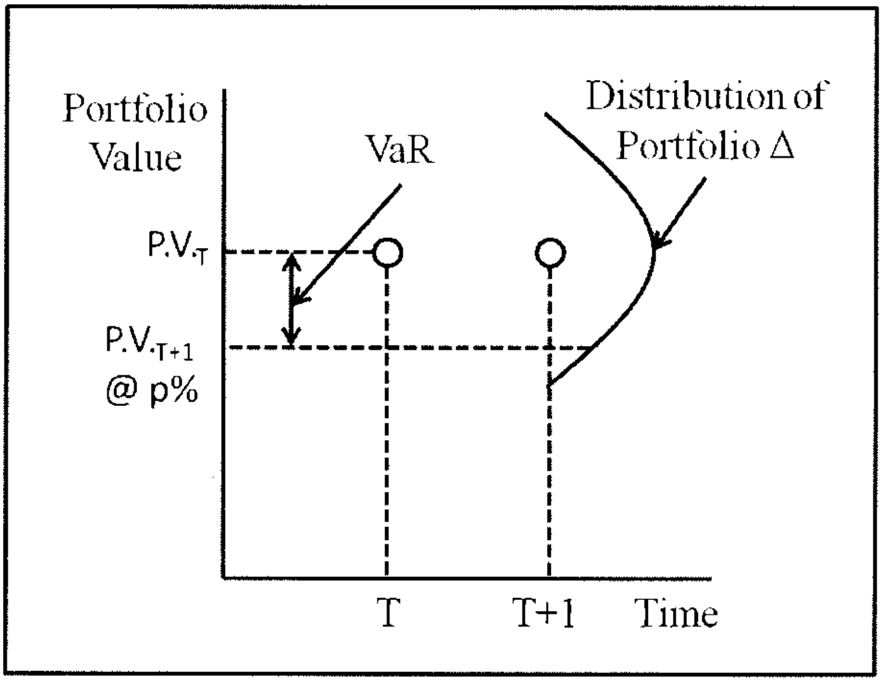

Figure 5 Value-at-Risk Concept

Value at Risk Computation

Jorion (2007) provides a general definition of VaR. VaR is the worst loss over a time period such that there is a low, prespecified probability that the realized loss will be larger. The following equation gives the definition in notation form, $P(L > VaR) \leq 1 - c$. In the equation, c is the confidence level, L is the loss in absolute value and VaR is the value at risk in absolute value. A critical implication of this definition is that two quantitative factors, the confidence level and the time horizon, need to be determined to give a precise definition to a firm's own value at risk.

Steps to Computing Value At Risk

Jorion (2007) identifies five steps in the computation process. The following steps are: marking the portfolio to market, measuring the dispersion of the market risk variables, determining the time horizon, determining the confidence level and, finally, reporting the worst, probable loss by using the information from the previous steps to create a probability distribution of profit/loss. This distribution is then used to determine the downside loss, or the value at risk.

Marking an asset to market is an important element of the margin accounting system for exchange-traded derivatives contracts. A derivative is marked-to-market when "it is valued on the basis of closing prices. The "marked-to-market" value represents the amount of money that a trader can expect to receive or pay when he unwinds the position (Butler, 1999, p. 231)." Thus, the first computational step is to calculate the current portfolio value determined by the market.

The second step requires identifying the relevant market risk variables and collecting historical prices for them. It is necessary to calculate historical rates of return from period to period prices with the selection of period length depending on the availability of price data. Allen, Boudoukh and Saunders (2004) identify three methods of calculating rates of return: absolute price changes, arithmetic returns and logarithmic returns. In the notation of the following methods, *t* is the time period and *p* is the price. Absolute price changes can be expressed as $\Delta P_{t,t+1} = p_{t+1} - p_t$. Arithmetic returns can be expressed as $R_{t,t+1} = \frac{(p_{t+1} - p_t)}{p_t}$. Logarithmic returns can be expressed as $r_{t,t+1} = \ln(\frac{p_{t+1}}{p_t})$. Allen, Boudoukh and Saunders (2004) state that the method of calculating rates of returns must provide a stationary time series and be time-consistent. Stationarity is important because to properly model the temporal dynamics of returns, changes in returns need to be equally likely across time. Time-consistency is also important because returns need to be aggregated across time, allowing single period returns to be converted into multi-period returns. Time-consistency is not a problem when rates of return are small, as the difference between arithmetic returns and logarithmic returns will be small. However, when returns are large or the time horizon is long, the difference between the two methods becomes apparent (Jorion, 2007).

Absolute price changes do not satisfy either the stationarity or time-consistency requirement. Arithmetic returns do provide a stationary time series but are not time-consistent. Logarithmic returns provide a stationary time series capable of being aggregated across time. Also, if logarithmic returns are normally distributed then the underlying prices will be log normally distributed, thus precluding negative prices (Jorion, 2007). Once a time series of historical rates of return is generated, the series can be used to determine the dispersion of the market variables or construct simulations to determine dispersion.

Thirdly and fourthly, the quantitative parameters; time horizon and confidence limit, need to be selected. Lastly, the information from the previous steps is used to generate a probability distribution of profit/loss. The last step is crucial as there are different methods of generating distributions which then determine the VaR of a portfolio. The advantages and limitations of each method will be explained later in the chapter along with a discussion of the selection of the quantitative parameters.

Quantitative Parameter Decisions

As mentioned earlier in chapter 3, the quantitative parameters necessary to define a specific VaR are the time horizon and confidence level. Generally, the risk measure increases with a longer time horizon and a greater confidence level. While describing the issues related to the quantitative parameters, it is important to remember that VaR is a benchmark for relative cross-sectional or temporal judgments. Cross-sectional judgments include one entity's risk measure relative to another. Entities within a firm extend from a single trader, a single business unit or the entire firm. Temporal judgments include the risk measure relative to historical risk measures or the risk measure relative to historical mark-to-market portfolio values (Duffie & Pan, 1997). The selection of the time horizon and confidence level depends on a firm's unique situation, in terms of their risk appetite and markets traded. The consistency of the quantitative parameters, both temporally and cross-sectionally, is important so that risk managers have a consistent benchmark across different markets and time.

Jorion (2007) explains that the selection of the quantitative parameters is determined by the characteristics of the assets contained in the portfolio. If the risk measure is used to determine capital buffers, the time horizon should correspond to the time required to take corrective measures and the firm's risk appetite should determine the confidence level. Typically, the horizon reflects the maximum time required to orderly liquidate the portfolio or hedge market risk variables. The extent of these actions is determined by a firm's risk appetite and the nature of the markets traded.

Processors commonly use the more liquid futures markets to establish forward purchasing and sales prices. The absence of hedging instruments eliminates a processor's ability to hedge or cross-hedge to mitigate price risk. With no liquid derivatives market available, purchasing and sales strategies cannot be hedged. In addition, cash market positions cannot be liquidated in a timely manner as these are illiquid markets. As a result, agricultural processors purchasing or selling commodities in which there are no futures markets should require considerably longer time horizons. Conversely, merchandising firms involved in markets with hedging instruments require a shorter time horizon.

Firms often select a daily risk measure as it is consistent with their daily profit and loss measures. This facilitates the comparison of risk measures with profit and loss measures, giving the firm a better understanding of market risk. An important assumption of the computation is that the current portfolio remains unchanged during the holding period (Linsmeier & Pearson, 1996). A consequence of this is as the horizon lengthens the significance of the risk measure declines.

Another important consideration for selecting the time horizon is the common practice of scaling volatility. Often, risk is measured at a short horizon and then converted to longer horizons by the square root of time method of scaling volatility (Diebold, Hickman, Inoue, & Schuermann, 1996). This method can be expressed as $\sigma_{t+h} = \sigma_t\sqrt{h}$ where h is the number of trading days. Converting a longer period volatility into a shorter period is defined by the expression $\sigma_{t-h} = \frac{\sigma_t}{\sqrt{h}}$. This method is prevalent in the financial industry with the 1996 amendment to the Basel Accord prominently featuring it. Diebold et al. (1996) state that the scaling rule is contingent upon returns being independently and identically distributed. If returns are either autocorrelated or conditionally heteroskedastic, then returns are not independently or identically distributed. Even when returns are not independently and identically distributed, scaling volatility produces results that are on average correct.

Computational Distributions

Non-Parametric Distributions

The non-parametric methods make no distributional assumptions as the distribution is fully valued across the entire distribution of underlying portfolio changes. The portfolio value at the end of the time horizon is expressed as $W = W_0(1 + R)$ where W_0 is the initial portfolio value and R is the rate of return. Given a confidence level c, the cut-off portfolio value is found by the following equation $W^* = W_0(1 + R^*)$ where R^* is the cut-off return value (Jorion, 2007).

Jorion (2007) defines the most general distributional form used to derive the value at risk from the future portfolio value $f(w)$ probability distribution in the following integral equation.

$$c = \int_{W^*}^{\infty} f(w)dw$$

At a specified confidence level c, there is a corresponding worst possible realization of W^* such that the probability of exceeding W^* is c. Alternatively, the probability of a realization lower than W^* is expressed as $p = P(w \leq W^*)$. The probability of such an occurrence corresponds to $1 - c$ as shown in the following equation (Jorion, 2007).

$$1 - c = \int_{-\infty}^{W^*} f(w)dw = P(w \leq W^*) = p$$

In words, the area of the integral from $-\infty$ to W^* must equal $p = 1 - c$. In the equation, no standard deviation was used. This allows the equation to be used for a discrete or continuous distribution (Jorion, 2007). Figure 6 shows a histogram of a non-parametric distribution.

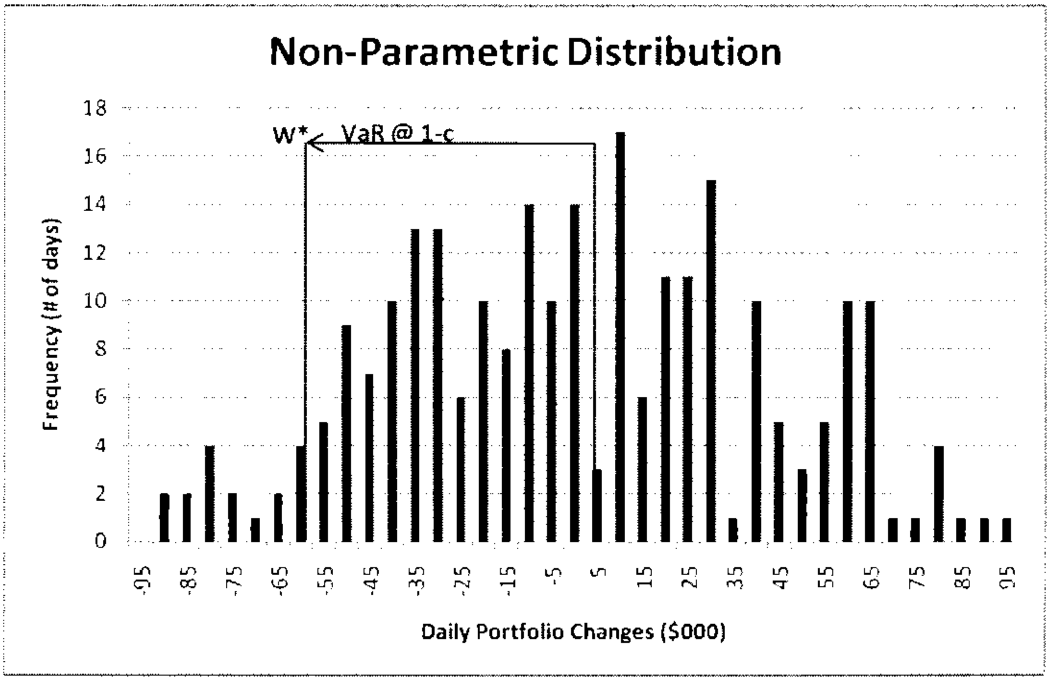

Figure 6 Non-Parametric Value-at-Risk

Jorion(Jorion, 2007) describes two different methods of calculating the value at risk, relative and absolute value at risk. The relative VaR is the probable dollar loss relative to the mean of the ending portfolio distribution as shown in the following equation.

$$VaR(mean) = E(W) - W^{*} = -W_0(R^{*} - \mu)$$

The absolute VaR is calculated without regard to the mean of the ending portfolio distribution as shown in the following equation.

$$VaR(zero) = W_0 - W^{*} = -W_0 R^{*}$$

Parametric Distributions

The parametric distribution simplifies the computation process by making a distributional assumption, most often the normal distribution. Instead of identifying the quantile of an empirical distribution, the parametric method uses a multiplicative factor to identify the possible downside loss of a portfolio.

First, a general portfolio distribution *f(w)* needs to be transformed into a standard normal distribution $\Phi(\in)$ with a mean of zero and standard deviation of one. The cutoff portfolio value is expressed as $W^{*} = W_0(1 + R^{*})$ where W^{*} is the portfolio cutoff value, W_0 is the initial portfolio value and R^{*} is the cutoff return required to produce W^{*}. In general, R^{*} is negative but should be reported as an absolute value, $-|R^{*}|$. The standard normal deviate, also called the multiplicative factor, can be expressed as $-\alpha = \frac{-|R^{*}|-\mu}{\sigma}$ where μ is the mean and σ is the standard deviation of the rate of return. By re-arranging the equation to calculate the standard normal deviate, the cut-off return value can be calculated by the expression $R^{*} = -\alpha\sigma + \mu$ (Jorion, 2007). This equation is similar to Baumol's equation (Baumol, 1963) for calculating the lower confidence limit of losses, $L = E - K\sigma$. In Baumol's equation, E is the expected return, K is a constant determined by risk appetite and σ is the standard deviation. Where Baumol's equation calculates the lower confidence limit of losses, the equation calculates R^{*}, or the cut-off rate of return value. Using the above information concerning W^{*} and R^{*}, the non-parametric distribution is shown to be equivalent to the standard normal distribution (Jorion, 2007).

$$1 - c = \int_{-\infty}^{W^{*}} f(w)dw = \int_{-\infty}^{-|R^{*}|} f(r)dr = \int_{-\infty}^{-\alpha} \Phi(\in)d \in$$

For a specified probability p, there is a corresponding standard normal deviate α. Therefore, calculating the VaR requires defining the standard normal deviate α such that the area to the left is found to be equal to 1 - c (Jorion, 2007).

$$p = N(x) = \int_{-\infty}^{x} \Phi(\in)d \in$$

To calculate the value at risk relative to the mean, the following equation is used (Jorion, 2007).

$$VaR(mean) = -W_0(R^* - \mu) = W_0 \alpha \sigma \sqrt{\Delta t}$$

In the previous equation, $\sqrt{\Delta t}$ is the time aggregation adjustment which is discussed in the following section. In words, the relative VaR is the beginning portfolio multiplied by the standard deviation of the portfolio distribution, the multiplicative factor and a time aggregation factor. The multiplicative factor is determined by a firm's risk appetite and corresponds to the specified confidence level. Figure 7 shows the parametric distribution in graphical form.

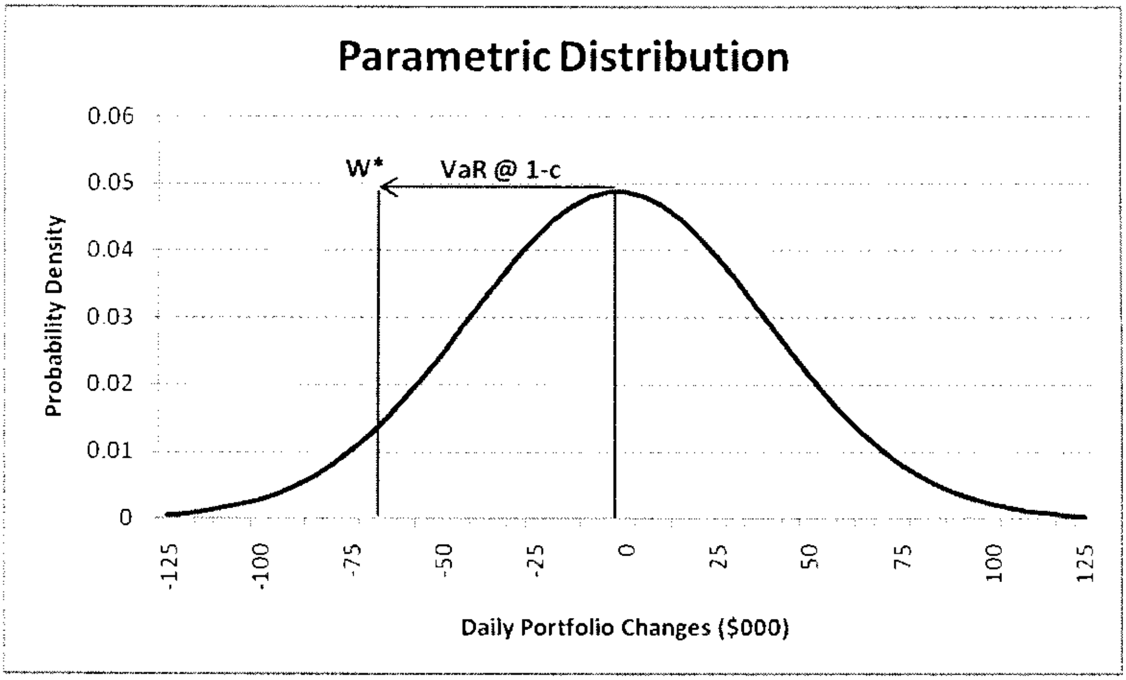

Figure 7 Parametric Value-at-Risk

The absolute VaR provides a measure in terms of absolute dollar losses. To calculate VaR relative to zero, or the absolute value at risk, the following equation is used (Jorion, 2007).

$$VaR(zero) = -W_0R^* = W_0(\alpha\sigma\sqrt{\Delta t} - \mu\Delta t)$$

Value at Risk Methods

Exposure to market risk variables potentially produce losses. The distribution of these losses is important because the distribution's shape determines the dispersion of assets' risk, thus producing more variability in the portfolio distribution. There are two models for determining exposure to risk: parametric and non-parametric. The parametric method employs local valuation in which the portfolio is valued once and the local derivative determines possible movements. The non-parametric method fully re-prices the portfolio over the entire range of values (Jorion, 2007).

There are two sources for potential gains and losses. One being exposures to market risk variables and the other being the positions held by the firm. Market risk exposures are not within the control of a firm but positions can be liquidated or hedged (Jorion, 2007). These two exposures are combined to generate the portfolio distribution, which is used to calculate the VaR measure. The different value at risk methods available make different assumptions in regards to the modeling of both positions and risk variables. When combined, the portfolio distribution can be generated using three main techniques: parametric distributions, historical simulation distributions and Monte Carlo simulation distributions (Jorion, 2007).

Characteristics of the Parametric Method

The parametric method calculation uses quantitative parameters to define the assumed portfolio distributions. The method has a number of limitations due to its many assumptions. A common assumption is that the logarithmic returns of market risk variables are normally distributed. This assumption is plausible due to the central limit theorem. The central limit theorem states that "if there are a large number of independent and identically distributed random variables, then the distribution of their sum tends to be a normal distribution as the number of such variables increases indefinitely (Gujarati & Porter, 2010)." The assumption of normality implies that a portfolio is a linear combination of each of its assets' returns. As a result, the method assumes that each market risk variable is normally distributed and the joint distributions between the variables are normal (Jorion, 2007).

Non-normality of price change distributions was first noted by Benoit Mandelbrot. In his research, he states, "the empirical distributions of price changes are usually too "peaked" to be relative to samples from Gaussian populations," adding further, "the tails of the distributions of price changes are in fact so extraordinarily long that the sample second moments typically vary in an erratic fashion (Mandelbrot, 1963)." This early observation has repercussions for risk modeling. If returns are skewed and/or leptokurtic, the result is that the assumption of normality insufficiently captures distributional tail behavior (Rachev, Menn, & Fabozzi, 2005). Also, as mentioned earlier, the parametric method implies that a portfolio is a linear combination of each of its assets' returns. The accuracy of the measure decreases with the presence of instruments with non-linear payoffs, such as option or other more exotic derivatives. The method uses local valuation to measure the exposures of non-linear instruments. This method, also called the delta-normal method, measures risk by valuing the initial position and using the local derivative as a linear approximation of possible variability. By assuming that a theoretical option premium is a linear exposure of the option delta, the method does not account for gamma, or the second derivative of the theoretical option premium with respect to the underlying asset's price (Jorion, 2007). The delta is a linear approximation of how the option value changes as the underlying futures price changes. However, gamma, or the curvature of the premium's value caused by the option' extrinsic value, is not incorporated. Figure 8 graphically presents gamma risk.

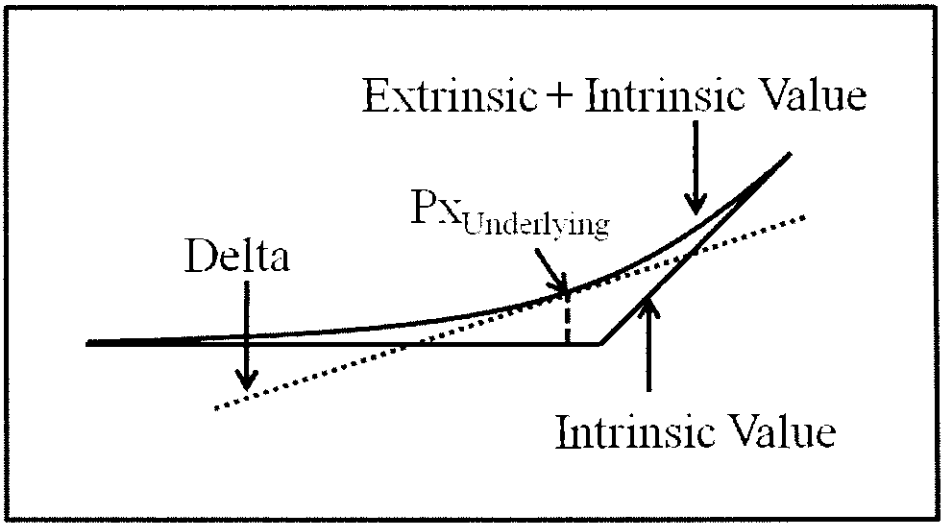

Figure 8 Long Call Payoff Diagram

There is a method of accounting for gamma in the parametric method, called the delta-gamma approximation. The method takes a second-order approach rather than a first order approach thereby accounting for gamma risk. However, the inclusion of second-order approximations makes the value at risk calculation more difficult and burdensome as squared or quadratic terms are involved (Dowd, 2002).

After explaining the limitations of the parametric method, there are obvious advantages. The two most important are that it is easy to implement due to the simple matrix calculations and that it is computationally fast due to the assumption of linear exposures. These two advantages make the method most appropriate for large portfolios with limited optionality due to it being a fast and efficient computation. The delta-gamma approach solves the problems of valuing optionality making it more suitable for fast computation of portfolios with substantial amounts of assets with non-linear payoffs (Jorion, 2007).

Characteristics of the Historical Simulation Method

The historical simulation method is a non-parametric approach requiring no specific assumptions about the market risk variables' distribution. The future portfolio distribution is fully valued across a range of values. The future portfolio distribution is constructed by taking the current portfolio of assets and applying the realized changes of historical returns over the data period. This creates a hypothetical future portfolio distribution with which one can identify the value at risk (Linsmeier & Pearson, 1996).

The main limitation of the historical method is the assumption that past market behavior predicts future market behavior. The forecasted portfolio distribution depends solely on the data set used. As a result, if the data used was during a period of low volatility then the method could fail to account for recent market dynamics. Also, the proper selection of the data period length is problematic. It is imperative to include only relevant market information. If the data period length is too long, irrelevant and aged information could distort the forecasted portfolio distribution. This potential problem is referred to as ghost effects and is also problematic in volatility estimation. Besides these weaknesses, the method does have a number of advantages. The method is simple, intuitive and easy to implement. The data required is readily available, either from public or in-house sources. Finally, since there are no specific parametric assumptions, the method can account for leptokurtic and/or skewed portfolio distributions (Dowd, 2002).

Characteristics of the Monte Carlo Simulation Method

Monte Carlo simulation's core characteristic is random number generation. An estimated distribution is selected that best approximates the changes in the market risk variables. It is a parametric method that generates pseudo-random return distributions from the estimated parametric distributions, fully valuing across the entire distribution range. First, parameters must be estimated from historical data. Then, random number generation is used to simulate fictitious price paths for the market risk variables by randomly drawing from a stochastic process (Jorion, 2007).

The main limitation of the method is the burdensome computational time required. As a portfolio has more assets included, the implementation becomes onerous. It is expensive to implement, both in terms of technological infrastructure and intellectual skills. Model risk also is a concern. If the specified stochastic process for the market risk variables is incorrect, the resulting portfolio distribution is likely to be inappropriate. It is important to test the robustness of the method by using sensitivity analysis (Jorion, 2007).

The method has a number of advantages that make it superior. Jorion states that, "Monte Carlo analysis is by far the most powerful method to compute VaR. For the risk factors, it is flexible enough to incorporate time variation in volatility or in expected returns, fat tails, and extreme scenarios (Jorion, 2007, p. 266)." Due to the portfolio being fully valued, the method accounts for nonlinear price exposures. The method also can account for complex interactions, such as copulas. It is most appropriate for accurate modeling of portfolios with substantial amounts of assets with non-linear payoffs or a longer time horizon (Jorion, 2007).

Stress Testing

VaR is measure of losses due to normal market movements. Abnormal market movements, losses larger than the VaR, are suffered with a pre-specified probability. Abnormal market environments are the concern of stress testing. To provide an example, if the specified probability is five percent and the time horizon is one day, one expects to suffer a loss greater than the value at risk one trading day out of twenty. The extent of the losses during this abnormal day is completely outside of the scope of the value at risk methodology. Also, there are periods of market turmoil where the assumptions of the methodology are violated. In agricultural commodity markets, these periods could be caused by inclement weather or sudden changes in trade policy. The objective of stressing a portfolio is to non-probabilistically estimate potential losses during abnormal market environments where improbable price movements are a reality. Figure 9 graphically shows the region that VaR is measuring, the area within the confidence level, and the region that stress testing measures, the area outside of the confidence level.

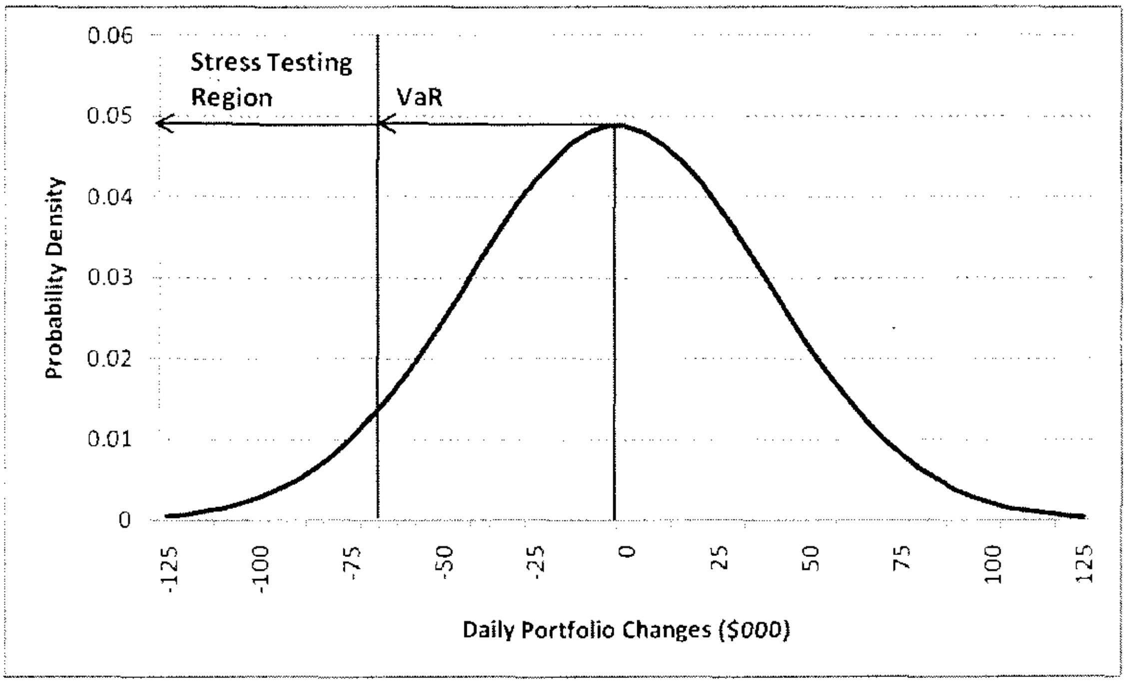

Figure 9 Stress Testing and Value-at-Risk Regions

Laubsch states that a stress test "should be relevant to current positions, consider changes in all relevant markets, examine potential regime shifts, spur discussion, consider market illiquidity and consider the interplay of market and credit risk (Laubsch, 1999, p. 24)." Of these, it is important to describe regime shifts. A regime shift is a situation in which the current parameters, especially correlation, break down. An example of this is the market's flight to safety in 1998 which led to the fall of Long Term Capital Management (Laubsch, 1999).

There are two primary methods of stress testing, scenario analysis and sensitivity analysis. Scenario analysis consists of generating market events, based on either history or anticipated realistic events, to evaluate the tail of the portfolio. Sensitivity analysis consists of shocking each market risk variable. To achieve this, incremental changes to each of the variables are applied to evaluate the sensitivity of the portfolio to each variable (Laubsch, 1999).

The objective of VaR is to determine the dispersion of profit/loss and use it to identify downside loss in a single, statistical dollar number. Stress testing focuses on losses greater than the downside loss measure, providing an understanding of a firm's risk during improbable market conditions. In this manner, a firm is able to identify vulnerabilities to catastrophic risk. Stress testing should be viewed as a necessary complement to the VaR methodology and not a replacement. Jorion states, "[stress testing provides] useful information, but only after the rest of the distribution has been specified (Jorion, 2007, p. 374)."

Coherent Risk Measures

Artzer et al. (1999) developed a series of axioms which determine whether a risk measure is coherent. A risk measure is coherent if it satisfies the following properties:

Sub-additivity – $\rho(X) + \rho(Y) \leq \rho(X + Y)$

Homogeneity – $\rho(tx) = t\rho(X)$

Monotonicity – $\rho(X) \geq \rho(Y)$, if $X \leq Y$

Risk-free Condition – $\rho(X + n) = \rho(X) - n$

Where X and Y are the future values of two portfolios and ρ is a risk measure.

Together, homogeneity and monotonicity imply that the risk measure ρ is convex. The risk-free condition ensures that the addition of n to the portfolio decreases the portfolio risk by the same amount (Dowd, 2002). Dowd states that, "sub-additivity means that aggregating individual risks does not increase overall risk (Dowd, 2002, p. 27)." Dowd explains that if a risk measure is sub-additive, then aggregating risks gives an overestimate of an aggregated portfolio's risk. An overestimated aggregated risk measure provides a conservative estimate of combined risk. If a risk measure does not satisfy sub-additivity, aggregating risks produces an underestimate of combined risks (Dowd, 2002). Generally, the VaR methodology is not sub-additive unless the implausible assumption that returns are normally distributed is imposed.

The most common coherent risk measure is expected tail loss, also called conditional VaR (Dowd, 2002). The expected tail loss is the expected value of losses, L, conditional upon whether they are in excess of the value at risk, $ETL = E(L|L > VaR)$. The main attraction of this methodology is that it provides a probabilistic estimate of the portfolio distribution's tail behavior, whereas VaR requires stress testing to non-probabilistically estimate portfolio losses in excess of the VaR measure.

From Value-At-Risk to Margin-At-Risk

Whereas VaR is a measure of the future change in a portfolio of assets given a specified probability and time horizon, MaR is a measure of the future margin given a specified probability and time horizon. MaR measures the potential loss in the gross or net margin of processing inputs into outputs. Also, MaR gives an indication of the amount of capital necessary to cover losses of production over the time horizon. This is similar to VaR being used to give an indication of capital necessary to cover trading losses over the time horizon. MaR can also be used to assess the effectiveness of different hedging and purchasing strategies, changes in production capacity and changes in the efficiency of the production process. The MaR concept is shown graphically in Figure 10.

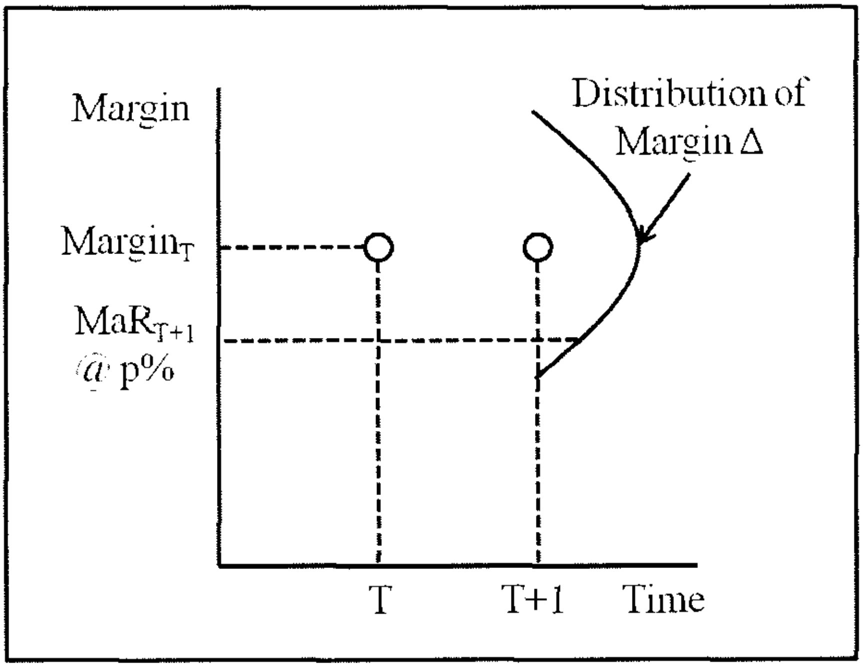

Figure 10 Margin-at-Risk Concept

CHAPTER IV. MODEL AND EMPIRICAL PROCEDURES

Introduction

Flour milling is a mature, low margin industry of overcapacity. Margins depend primarily on the cost of procuring the necessary inputs but also on microeconomic factors influencing consumers of flour. Microeconomic factors which determine the demand for flour, thus the amount consumers are willing to purchase at a given price level, include preferences, disposable income and availability of substitutes.

This chapter gives an explanation of prototypical flour milling scenarios. The scenarios analyzed are from the perspective of a North American flour mill in a competitive market environment and an international flour mill in a regulated market with import requirements. The model employed is explained and the data is described statistically. Different distributional procedures, both in regards to individual distributions and joint distributions between market risk variables, are discussed. Finally, the simulation procedures are described.

Prototypical Milling Scenarios

There are three scenarios explored in this thesis. The first scenario is a representative flour mill located in Minneapolis, Minnesota. Since the representative mill is located in the United States, the market environment is competitive with no government intervention. The second scenario is a representative South Korean flour mill with wheat import requirements and government intervention in output pricing. Also, the inputs and outputs are priced in U.S. Dollars. The third scenario is the same as the second except with the outputs being priced in South Korean Won and the inputs being priced in U.S. Dollars. This adds exchange rate risk to the last scenario.

Scenario #1-North American Competitive Market

.In the competitive North American market scenario, a flour mill located in Minneapolis, Minnesota is chosen as the prototypical entity. Concerning the inputs to flour milling, futures and basis are identified as market risk variables. These inputs are processed into the outputs of milling, flour and mill feeds. These two outputs are identified as market risk variables. In this scenario, all market risk variables are denominated in U.S. dollars. A number of technical assumptions are made. A flour extraction rate of 72%, an industry standard, is chosen. With a flour extraction rate of 72%, 100 pounds of wheat produce 72 pounds of flour and 28 pounds of mill feeds. The daily milling capacity is assumed to be 15,000 hundredweights of flour a day. Also, it is assumed that a mill operates 21 days per month and is operating at full capacity. Thus, the representative mill produces 315,000 hundredweight of flour per month and 122,500 hundredweight of mill feeds per month from 729,167 bushels of wheat. It is important to note that the MaR method assumes that input and output quantities are assumed to be constant over the time horizon period, which is 1 month.

Technical assumptions can be relaxed by assigning distributions to the flour extraction rate and amount of flour produced per day. By assigning distributions to the technical aspect of flour milling, a greater amount of margin variability could be factored into the analysis. However, this analysis focuses on the effect of market risk variables' behavior on the gross milling margin.

In this scenario, it is assumed that the representative mill is producing only one flour over the time period, 13.5% Protein Baker's Standard Patent Flour. To produce such a flour, the representative mill has to procure a combination of 14% Protein #1 Dark Northern Hard Red Spring Wheat and 15% Protein #1 Dark Northern Hard Red Spring Wheat in equal amounts from the Minneapolis terminal market, assuming that 1% of protein is lost during the milling process. Table 1 specifies the input and output quantities of the milling process while Table 2 presents the procurement and marketing strategies of this scenario.

Table 1 Scenario #1-Milling Input and Output Quantities

	Input and Output Quantities			
	Input		**Outputs**	
	14% DNS (bu)	**15% DNS (bu)**	**13.5% Flour (cwt)**	**Mill feeds (cwt)**
Quantity	364,583	364,583	315,000	122,500

Table 2 Scenario #1-Procurement and Marketing Strategies

Wheat Procurement Strategies		
	Futures Px	**Basis**
Short Cash	Random	Random
Hedged Futures	Fixed	Random
Basis Contract	Random	Fixed
Forward Contract	Fixed	Fixed

Marketing Strategies		
	Flour Px	**Mill feeds Px**
Flour sold	Fixed	Random
Mill feeds sold	Random	Fixed

The objective of this analysis is to assess the effects of different procurement and marketing strategies on the gross milling margin, using the MaR method as a metric. Table

2 describes the effects of different strategies on market risk variables, both on the procurement side (inputs) and the marketing side (outputs).

The base procurement and marketing scenario assumes that flour is sold one month in advance as shown in Table 3. The objective of this scenario is to determine which procurement and marketing strategies or which combination of procurement and marketing strategies mitigates the market risk exposure of the gross milling margin. This scenario reflects common practice in the flour milling industry. Peck (1978) explains that flour consumers often purchase several months of flour requirements ahead at a single time. Flour prices change intra-daily with the price of cash wheat and the price of mill feeds. When the price of flour is fixed, a flour mill seeks to mitigate unfavorable changes in the cost of cash wheat requirements. Thus, the flour miller's goal is to identify which risk management strategies provide the best protection for already low margins.

Table 3 Scenario #1-Flour Fixed Price Strategies

Base Procurement and Marketing Scenario Flour Sold in Advance				
	Input Risk		**Output Risk**	
	Futures Px	**Basis**	**Flour Px**	**Millfeeds Px**
Short Cash	Random	Random	Fixed	Random
Hedged Futures	Fixed	Random	Fixed	Random
Basis Contract	Random	Fixed	Fixed	Random
Forward Contract	Fixed	Fixed	Fixed	Random
Short Cash & Mill feeds sold	Random	Random	Fixed	Fixed
Hedged futures & Mill feeds sold	Fixed	Random	Fixed	Fixed
Basis Contract & Mill feeds sold	Random	Fixed	Fixed	Fixed
Forward Contract & Mill feeds sold	Fixed	Fixed	Fixed	Fixed

The alternative procurement and marketing scenario assumes that flour is not sold in advance. Although it is more prevalent for a mill to sell flour in advance, the situation in which flour inventories are exposed to price risk could arise. Table 4 presents the strategies involved with the alternative scenario.

Table 4 Scenario #1-Flour Random Price Strategies

Alternative Procurement and Marketing Scenario Flour Not Sold in Advance				
	Input Risk		**Output Risk**	
	Futures Px	**Basis**	**Flour Px**	**Millfeeds Px**
Short Cash	Random	Random	Random	Random
Hedged Futures	Fixed	Random	Random	Random
Basis Contract	Random	Fixed	Random	Random
Forward Contract	Fixed	Fixed	Random	Random
Short Cash & Mill feeds sold	Random	Random	Random	Fixed
Hedged futures & Mill feeds sold	Fixed	Random	Random	Fixed
Basis Contract & Mill feeds sold	Random	Fixed	Random	Fixed
Forward Contract & Mill feeds sold	Fixed	Fixed	Random	Fixed

Scenario #2-International Regulated Market

A South Korean flour mill is chosen as the prototypical flour mill with wheat import requirements. Also, the outputs, flour and mill feeds, are held at a fixed level which is determined by the government. It is common in many countries for the government to regulate the flour milling industry through administrative price fixing, establishment of maximum margins or provision of input subsidies. This is done because flour is considered to be a socially important food staple, satisfying the basic nutritional needs of a country's population (Agribusiness Handbook- Wheat Flour, 2009).

The input and output quantities are the same as the North American competitive market scenario. However, in this scenario, 11% protein noodle flour is produced. In South Korea, noodles account for 40% of total flour use and typical protein levels for the flour range from 8% to 11% (Faridi & Faubion, 1995). 11% protein noodle flour requires 12% protein hard red winter wheat, assuming 1% protein is lost during the milling process. In this scenario, all inputs and outputs are denominated in U.S. Dollars. This eliminates exchange rate risk, an important source of risk for an international grain importer. Table 5 presents the input and output quantities for this scenario.

Table 5 Scenario #2-Milling Input and Output Quantities

	Input and Output Quantities		
	Input	**Outputs**	
	12% HRWW (bu)	**11% Flour (cwt)**	**Mill feeds (cwt)**
Quantity	729,167	315,000	122,500

The wheat procurement strategies are the same as the North American competitive market scenario. However, due to South Korea being an importer of grain, it is necessary to procure the necessary input requirements from an exporting nation. The grain then needs to be transported from the origin to the destination by ocean vessels. Along with futures price and basis risk, ocean freight rate risk is incorporated. There are two different choices for ocean transportation that designate the responsibilities of the buyer and the seller in this thesis. The first is Free on Board (FOB). FOB is bought at the origin with the buyer being responsible for ocean transportation to the destination. The grain is delivered and as it is poured into the ocean vessel's hold, the responsibility of the seller ends. The other is Cost and Freight (C&F). C&F contractually obligates the seller to deliver the commodity from the origin to the destination (Importer Manual, 2004). In this scenario, the differences between these two have important ramifications. As was noted in Chapter 1, ocean freight rates are volatile markets. By obligating the seller of grain to take the responsibility of ocean transportation, a grain importer is taking measures to limit his exposure to the volatile freight market. Table 6 describes the effect of these different risk management strategies on the market risk variables.

Table 6 Scenario #2-Procurement and Transportation Strategies

Wheat Procurement Strategies		
	Futures Px	**Basis**
Short Cash	Random	Random
Hedged Futures	Fixed	Random
Basis Contract	Random	Fixed
Forward Contract	Fixed	Fixed

Transportation Strategies	
	Ocean Freight
FOB	Random
C&F	Fixed

The objective of this scenario is to identify which risk management strategies most effectively mitigate the risk inherent in buying and transporting grain. By utilizing a cost and freight procurement strategy, a processor can bypass the risk of higher freight rates. However, if freight rates drop, the processor will be locked into higher freight rates than the current market. Table 7 displays the different risk management strategies and combinations of them which are used in the analysis.

The last scenario is the same as the second, a South Korean flour mill with wheat import requirements. However, in the previous scenario, exchange rate risk was not incorporated. To fully reflect the realities of a grain importer, exchange rate fluctuations need to be a part of the analysis. In this scenario, it is assumed that the inputs are priced in U.S. Dollars but the outputs are priced in South Korean Won. The outputs are still assumed to be fixed by the government but are exposed to both advantageous and disadvantageous changes in the South Korean Won to U.S. Dollar exchange rate.

Table 7 Scenario #2-Outputs Fixed Price Strategies

Procurement and Marketing Scenario Flour and Mill feeds Fixed by Government			
	Input Risk		
	Futures Px	Basis	Ocean Rates
Short Cash	Random	Random	Random
Hedged Futures	Fixed	Random	Random
Basis Contract	Random	Fixed	Random
Forward Contract	Fixed	Fixed	Random
Short Cash & C&F	Random	Random	Fixed
Hedged futures & C&F	Fixed	Random	Fixed
Basis Contract & C&F	Random	Fixed	Fixed
Forward Contract & C&F	Fixed	Fixed	Fixed

Scenario #3- International Regulated Market With Forex Risk

Table 8 displays the different risk management strategies and combinations of each used in this analysis.

Empirical Model

As mentioned in Chapter 3, Jorion states, "Monte Carlo analysis is by far the most powerful method to compute VaR (Jorion, 2007, p. 266)." The analysis utilizes Monte Carlo simulation procedures due its advantages discussed in Chapter 3. A one month time horizon and 90% confidence level were chosen for the quantitative parameters. One month was selected due to the nature of flour milling. A flour mill cannot make risk management decisions on a daily basis. Due to the nature of its production process, one month provides a reasonable time horizon for a prototypical mill to take measures to mitigate market risk exposures. A 90% confidence level is chosen as it is a common benchmark in "at-risk" analysis.

Table 8 Scenario #3-Outputs Fixed Price Strategies

Procurement and Marketing Scenario Flour and Mill feeds Fixed by Government With Exchange Rate Risk				
	Input Risk			**Output Risk**
	Futures Px	**Basis**	**Ocean Rates**	**Exchange Rate**
Short Cash	Random	Random	Random	Random
Hedged Futures	Fixed	Random	Random	Random
Basis Contract	Random	Fixed	Random	Random
Forward Contract	Fixed	Fixed	Random	Random
Short Cash & C&F	Random	Random	Fixed	Random
Hedged futures & C&F	Fixed	Random	Fixed	Random
Basis Contract & C&F	Random	Fixed	Fixed	Random
Forward Contract & C&F	Fixed	Fixed	Fixed	Random

The basic structure of the model is expressed by the following equation.

$$\pi = (Q_{FL}P_{FL} + Q_{MF}P_{MF}) - ((Q_W(P_F + B))$$

In the equation, π is the gross milling margin. For revenue being generated, Q_{FL} is quantity of flour produced, P_{FL} is the price of flour, Q_{MF} is quantity of mill feeds produced and P_{MF} is the price. For the cost of inputs, Q_W is quantity of wheat procured, P_F is the futures price and B is the basis. By adding P_F and B, the local cash price is calculated.

For the North American competitive market scenario, the empirical model is expressed by the following equation.

$$\pi = \left(Q_{FL}\tilde{P}_{FL} + Q_{MF}\tilde{P}_{MF}\right) - ((Q_{W_{14}}\left(\tilde{P}_F + \tilde{B}_{14}\right) + (Q_{W_{15}}(\tilde{P}_F + \tilde{B}_{15}))$$

In the empirical models, a ~ denotes a market risk variable which is determined by distributions of price or rate changes generated by a Monte Carlo simulation procedure. For revenue being generated Q_{FL} is the quantity of 13.5% Baker's Standard Patent flour being produced, P_{FL} is the market price for 13.5% Baker's Standard Patent flour in Minneapolis, Q_{MF} is the quantity of mill feeds produced and P_{MF} is the price of mill feeds in Minneapolis. For the cost of inputs, Q_{W14} is the quantity of 14% protein hard red spring wheat required, P_F is the price of MGEX hard red spring wheat futures, B_{14} is the local basis in the Minneapolis terminal market for 14% protein hard red spring wheat, Q_{W15} is the quantity of 15% protein hard red spring wheat required and B_{15} is the local basis in the Minneapolis terminal market for 15% protein hard red spring wheat. Finally, the gross milling margin is π.

For the grain importer in a regulated market scenario, the empirical model is expressed by the following equation.

$$\pi = (Q_{FL}P_{FL} + Q_{MF}P_{MF}) - ((Q_{W_{12}}(\tilde{P}_F + \tilde{B}_{12} + \tilde{R}_O))$$

For revenue being generated, Q_{FL} is quantity of flour produced, P_{FL} is the price of 11% noodle flour in South Korea, Q_{MF} is quantity of mill feeds produced and P_{MF} is the price of mill feeds in South Korea. For the cost of inputs, Q_{W12} is the quantity of 12% protein hard red winter wheat required, P_F is the price of KCBT hard red winter wheat futures, B_{12} is the local basis in the Pacific Northwest export market for 12% hard red winter wheat and R_O is the ocean freight rate. Finally, the gross milling margin is π. Note that flour and mill feed prices are not considered market risk variables. This is because it is assumed that the government has fixed the price of both.

For the grain importer in a regulated market with exchange rate risk scenario, the empirical model is expressed by the following equation.

$$\pi = \left(\left(\frac{Q_{FL} P_{FL_{₩}}}{\tilde{R}_{₩/\$}} \right) + \left(\frac{Q_{MF} P_{MF_{₩}}}{\tilde{R}_{₩/\$}} \right) \right) - ((Q_{W_{12}} (\tilde{P}_F + \tilde{B}_{12} + \tilde{R}_O))$$

In this equation, $R_{₩/\$}$ is the South Korean Won/United States Dollar exchange rate, $P_{FL₩}$ is the price of 11% noodle flour in South Korea denominated in South Korean Won and $P_{MF₩}$ is the price of mill feeds in South Korea denominated in South Korean Won.

Distribution and Simulation Procedures

Logarithmic returns were calculated for each of the market risk variables. The logarithmic return provides a measure of the rate of change from time period to time period. Logarithmic returns were calculated by logarithmically transforming the ratio of the price in one period and the price in the previous period, $r_{t,t+1} = \ln(\frac{p_{t+1}}{p_t})$. This method of calculating price changes was used due to the advantages discussed in Chapter 3. In the analysis, each of the market risk variables' series of logarithmic returns were "fit" to an appropriate continuous distribution using the Vose ModelRisk software package. Also, the copulas describing the structure of dependence between the market risk variables were selected using the same procedure. The software utilizes maximum likelihood method to estimate the most likely distributional parameters given the actual data (Brooks, 2002). Specifically, an iterative process maximizes the log likelihood function. To rank the distributions that most likely correspond to the behavior of the data, Akaike Information Criterion (AIC) is used. The AIC can be expressed with the following equation (Vose, 2010).

$$AIC = \left(\frac{n - 2k + 2}{n - k + 1}\right) - 2ln[L_{max}]$$

In the equation, n is the number of observations, k is the number of parameters being estimated and L_{max} is the maximized value of the log likelihood function.

While AIC provides a ranking of distributions, the most appropriate distribution must be selected by taking into consideration the nature of the data. An important factor is how well the selected distribution's tails correspond to the data.

Vose ModelRisk utilizes Monte Carlo sampling for its simulation procedure. A Monte Carlo simulation procedure is based on randomly drawing from a variable with a specified probability distribution. The numbers are considered "pseudo" random because they are generated from algorithms. A well designed algorithm should generate draws from a distribution that pass tests of independence (Jorion, 2007). Distributions were specified and then simulated to create "pseudo" random distributions of logarithmic returns for each market risk variable.

Model Data and Distribution Selection

The data for this thesis were aggregated from a variety of sources. The time period of the data is from January 2006 to November 2010, 58 observations in total. Since monthly values are the only data available, any values that were weekly or daily were converted into monthly averages. For the North American competitive market scenario, hard red spring wheat futures daily prices and Minneapolis 14% and 15% protein daily basis values were retrieved from the Minneapolis Grain Exchange website. 13.5% protein Baker's Standard Patent weekly flour prices in Minneapolis and mill feeds weekly prices in Minneapolis were taken from *Milling and Baking News*' Ingredient Market Trends sections from a number of issues. Table 9 presents the descriptive statistics of the price change data used in the scenario. Note the significant levels of positive skewness and kurtosis for futures, basis and flour prices. This is an indication that a normal distribution is a poor distribution to utilize in the analysis. Also, the basis for both 14% and 15% protein wheat exhibit the most volatility among the different variables.

Table 9 Scenario #1 Data (2006-2010)-Descriptive Statistics

Descriptive Statistics of Logarithmic Returns-Minneapolis (2006-2010)							
	Units	**Minimum**	**Maximum**	**Mean**	**St. Dev**	**Skewness**	**Kurtosis**
MGEX HRSW	\$/bushel	-0.204	0.422	0.011	0.104	0.863	6.485
MPLS 14% Basis	\$	-1.411	2.285	-0.003	0.555	0.890	7.682
MPLS 15% Basis	\$	-1.203	2.045	0.012	0.450	1.157	10.489
MPLS 13.5% Flour	\$/cwt	-0.202	0.389	0.007	0.095	0.824	6.682
MPLS Mill feeds	\$/Short Ton	-0.441	0.374	0.016	0.169	-0.497	3.320

Distributions were selected according to the procedure described earlier. Table 10 presents the distributions found most appropriate for the North American competitive market scenario from 2006 to 2010. The distributions used were the normal distribution, the Laplace distribution and the error function distribution. The normal distribution is defined by its mean and standard deviation. The Laplace distribution is similar to the normal distribution as it is symmetrical and is defined by its mean and standard deviation but has a sharper peak with fatter tails. It is becoming popular as of recently in financial modeling (ModelRisk Help, 2007). The error function distribution is derived from the normal distribution. This is done by setting the mean to zero and the standard deviation to $\frac{1}{(h\sqrt{2})}$.

Table 10 Scenario #1 Data (2006-2010)-Distribution Parameters

Distribution Parameters-Minneapolis (2006-2010)				
	Distribution	**Mean**	**St. Dev**	**h**
MGEX HRSW	**Normal**	0.011	0.104	-
	Laplace	0.008	0.101	-
MPLS 14% Basis	**Normal**	-0.003	0.555	-
	Laplace	-0.011	0.526	-
MPLS 15% Basis	**Normal**	0.012	0.450	-
	Laplace	-0.010	0.387	-
MPLS 13.5% Flour	**Normal**	0.007	0.095	-
	Laplace	0.004	0.095	-
MPLS Mill feeds	**Normal**	0.016	0.169	-
	Error Function	-	-	4.191

To estimate the dependence structure between variables, parametric copulas were used. The linear correlation coefficient is the normal copula's parameter. Table 11 presents the correlation coefficients for the multivariate normal copula. There exists a strong correlation of .847 between hard red spring wheat futures and flour price changes. As spring wheat futures prices are a primary component of pricing flour, this is expected. Also, there exists a strong correlation, .855, between the 14% and 15% protein PNW wheat markets. Since these markets are differentiated only by a protein premium, a strong correlation is to be expected as well.

The multivariate Student-t copula was determined to be the most appropriate dependence structure by the Akaike Information Criterion. The parameters of the Student-t copula include the degrees of freedom and the linear correlation coefficients. The multivariate Student-t copula will converge to a normal copula with higher degrees of freedom. However, for a smaller number of degrees of freedom, the Student-t copula has more dependence in the tail (ModelRisk Help, 2007). Table 12 presents the parameters to the copula. The correlation coefficients are the same as the normal copula; however, the inclusion of the degrees of freedom parameter changes the structure of dependence. In this case, the dependence in tails of the joint distribution will be stronger due to less degrees of freedom.

Table 11 Scenario #1 Data (2006-2010)-Normal Copula Parameters

	Correlation Matrix				
	MGEX HRSW	**MPLS 14% Basis**	**MPLS 15% Basis**	**MPLS 13.5% Flour**	**MPLS Mill feeds**
MGEX HRSW	1	-0.104	0.000	0.847	0.287
MPLS 14% Basis	-0.104	1	0.855	0.192	-0.107
MPLS 15% Basis	0.000	0.855	1	0.198	-0.045
MPLS 13.5% Flour	0.847	0.192	0.198	1	0.116
MPLS Mill feeds	0.287	-0.107	-0.045	0.116	1

Table 12 Scenario #1 Data (2006-2010)-Student-t Copula Parameters

Multivariate t Copula Parameters-Minneapolis (2006-2010)					
	Correlation Matrix				
	MGEX HRSW	**MPLS 14% Basis**	**MPLS 15% Basis**	**MPLS 13.5% Flour**	**MPLS Mill feeds**
MGEX HRSW	1	-0.104	0.000	0.847	0.287
MPLS 14% Basis	-0.104	1	0.855	0.192	-0.107
MPLS 15% Basis	0.000	0.855	1	0.198	-0.045
MPLS 13.5% Flour	0.847	0.192	0.198	1	0.116
MPLS Mill feeds	0.287	-0.107	-0.045	0.116	1
	Degrees of Freedom		3		

As Figure 11 illustrates, 2008 was an atypical year in terms of volatility for hard red spring wheat futures. In flour milling, futures price is the primary driver of procurement costs. As such, it is important to also analyze the scenario using data from after that period of volatility.

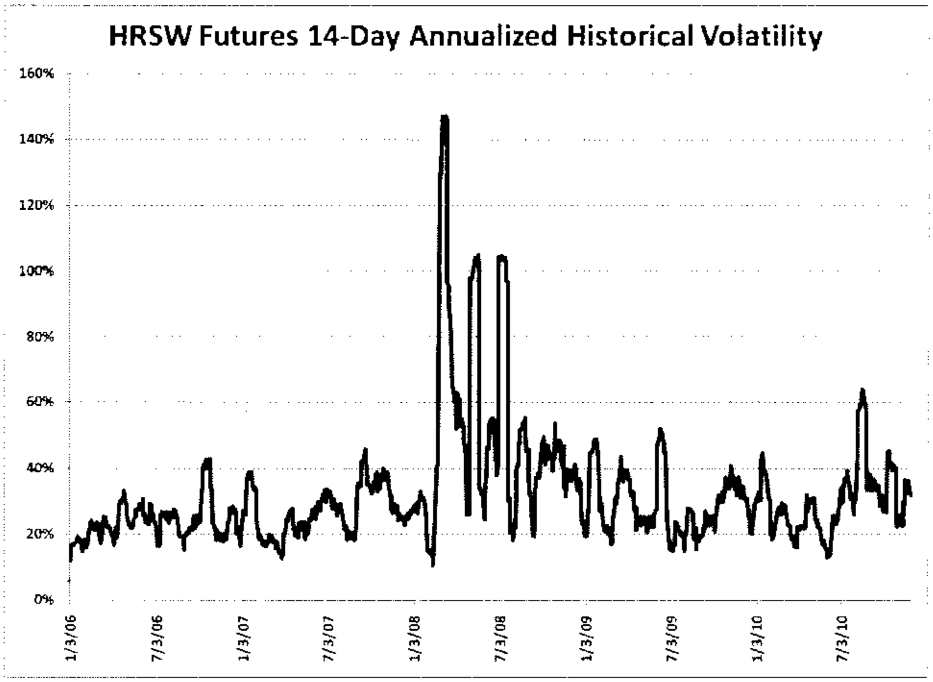

Figure 11 Hard Red Spring Wheat Futures Historical Volatility

Table 13 presents the descriptive statistics for price changes in the scenario from January 2009 to November 2010, 23 observations in total. Note the kurtosis levels for this sample period are less than the 2006 to 2010 period. Also, the standard deviation of futures, basis and flour prices are considerably less.

Table 13 Scenario #1 Data (2009-2010)-Descriptive Statistics

Descriptive Statistics of Logarithmic Returns-Minneapolis (2009-2010)							
	Units	**Minimum**	**Maximum**	**Mean**	**St. Dev**	**Skewness**	**Kurtosis**
MGEX HRSW	$/bushel	-0.164	0.177	0.009	0.078	-0.035	3.891
MPLS 14% Basis	$	-1.050	0.813	-0.029	0.381	-0.153	4.766
MPLS 15% Basis	$	-0.481	0.696	-0.010	0.231	1.008	6.375
MPLS 13.5% Flour	$/cwt	-0.134	0.136	0.004	0.068	0.049	3.258
MPLS Mill feeds	$/Short Ton	-0.387	0.374	0.005	0.156	-0.108	4.464

The most appropriate distributions were selected for each of the market risk variables. Table 14 presents the parameters for each of the distributions. Again, the distributions used were the normal, the Laplace and the error function.

Table 14 Scenario #1 Data (2009-2010)-Distribution Parameters

Distribution Parameters-Minneapolis (2009-2010)				
	Distribution	**Mean**	**St. Dev**	**h**
MGEX HRSW	**Normal**	0.009	0.078	-
	Laplace	-0.002	0.078	-
MPLS 14% Basis	**Normal**	-0.029	0.381	-
	Laplace	-0.070	0.385	-
MPLS 15% Basis	**Normal**	-0.010	0.231	-
	Laplace	-0.046	0.225	-
MPLS 13.5% Flour	**Normal**	0.004	0.068	-
	Laplace	-0.002	0.070	-
MPLS Mill feeds	**Normal**	0.005	0.156	-
	Error Function	-	-	4.632

Table 15 presents the parameters for the multivariate normal copula, which was determined to be the most appropriate by the selection procedure. During this time period, hard red spring wheat futures and flour price changes are still positively correlated but not to the same degree as the longer time period. The 14% and 15% PNW wheat markets still exhibit strong positive correlation.

Table 15 Scenario #1 Data (2009-2010)-Normal Copula Parameters

Multivariate Normal Copula Parameters-Minneapolis (2009-2010)					
	Correlation Matrix				
	MGEX HRSW	**MPLS 14%**	**MPLS 15%**	**MPLS 13.5%**	**MPLS Mill**
MGEX HRSW	1	-0.438	-0.335	0.543	0.323
MPLS 14% Basis	-0.438	1	0.828	0.430	0.006
MPLS 15% Basis	-0.335	0.828	1	0.447	0.068
MPLS 13.5% Flour	0.543	0.430	0.447	1	0.197
MPLS Mill feeds	0.323	0.006	0.068	0.197	1

For the grain importer scenarios, hard red winter wheat futures daily prices and Pacific Northwest 12% protein monthly basis values were obtained from the U.S. Wheat Associates. Ocean freight rates from the Pacific Northwest to Japan, a proxy for ocean freight rates to South Korea, were provided by the United State Department of Agriculture. Monthly South Korean Won/U.S. Dollar exchange rates were retrieved from the St. Louis Federal Reserve's Economic Research department. The fixed prices for 11% protein noodle flour and mill feeds in South Korea were obtained from industry contacts. Table 16 presents the descriptive statistics for the price change data used in both grain importer scenarios. 12% protein PNW basis exhibited the most variance followed by ocean freight rates. The South Korean Won/U.S. Dollar exchange rate exhibited a considerable amount of positive skewness while ocean freight rates were negatively skewed. Both exchange rate and ocean freight rates exhibited high kurtosis. This indicates a normal distribution is a poor distribution to utilize in the analysis of the scenario, especially for the 12% protein PNW market and PNW to Japan ocean freight rates.

Table 16 Scenario #2 and #3 Data-Descriptive Statistics

Descriptive Statistics of Logarithmic Returns-South Korea (2006-2010)							
	Units	**Minimum**	**Maximum**	**Mean**	**St. Dev**	**Skewness**	**Kurtosis**
KCBT HRWW	\$/bushel	-0.244	0.232	0.011	0.090	0.148	3.701
PNW 12% Basis	\$	-0.562	0.667	0.002	0.216	0.412	4.383
PNW-Japan Ocean Rates	\$/Metric Ton	-0.780	0.309	0.005	0.171	-1.760	9.973
Korean Won/US Dollar		-0.085	0.158	0.002	0.034	1.724	10.517

Table 17 presents the distributions selected for each of the market risk variables in the scenario. Two distributions not yet discussed were used for this scenario, the hyperbolic secant and the extreme value minimum distribution. The hyperbolic secant distribution is similar to the normal distribution as it is symmetric and defined by its mean and standard deviation. However, it has a kurtosis level of 5 instead of the normal distribution's kurtosis level of 3. The extreme value minimum distribution is negatively skewed, -1.1396. Also, it has a more peaked distribution with fatter tails than a normal distribution as its kurtosis level is 5.4. The equation for the probability density function of the extreme value minimum equation is presented below (ModelRisk Help, 2007). The parameters that define the distribution, a and b, are included in the table.

$$f(x) = \left(-\frac{1}{b}\right) \exp\left(\frac{x+a}{b}\right) \exp\left[-\exp\left(\frac{x+a}{b}\right)\right]$$

Table 17 Scenario #2 and #3 Data-Distribution Parameters

Distribution Parameters-South Korea (2006-2010)					
	Distribution	**Mean**	**St. Dev**	**A**	**B**
KCBT HRWW	**Normal**	0.011	0.090	-	-
	Laplace	0.001	0.093	-	-
PNW 12% Basis	**Normal**	0.002	0.216	-	-
	Hyperbolic Secant	-0.006	0.215	-	-
PNW-Japan Ocean Rates	**Normal**	0.005	0.171	-	-
	Extreme Value Min	-	-	0.078	0.135
Korean Won/US Dollar	**Normal**	0.002	0.034	-	-
	Laplace	0.000	0.030	-	-

Since there were two scenarios, the second incorporating exchange rate risk, each scenario needs to different dependence procedures. Table 18 presents the multivariate normal copula for the grain importer in a regulated market scenario. All variables have weak positive correlation.

An important part of the Clayton copula is Kendall's tau rank order correlation coefficient (τ). It measures the degree of correspondence between variables, much the same as Spearman's rho correlation coefficient. The relationship between Kendall's tau and the alpha (α) parameter with respect to the Clayton copula is expressed in the equation below (ModelRisk Help, 2007).

Table 18 Scenario #2 Data-Normal Copula Parameters

Multivariate Normal Copula Parameters-South Korea (2006-2010) Correlation Matrix			
	KCBT HRWW	**PNW 12% Basis**	**PNW-Japan Ocean Rate**
KCBT HRWW	1	0.129	0.348
PNW 12% Basis	0.129	1	0.217
PNW-Japan Ocean Rates	0.348	0.217	1

$$\hat{\alpha} = \frac{2\tau}{1-\tau}$$

Table 19 presents the multivariate Clayton copula parameters, which was determined to be the most appropriate by the selected procedure. An important characteristic of the Clayton copula is that it exhibits stronger dependence in the downside tail than in the upside tail.

Table 19 Scenario #2 Data- Clayton Copula Parameters

Multivariate Clayton Copula Parameters-South Korea (2006-2010) Correlation Matrix			
	KCBT HRWW	**PNW 12% Basis**	**PNW-Japan Ocean Rate**
KCBT HRWW	1	0.129	0.348
PNW 12% Basis	0.129	1	0.217
PNW-Japan Ocean Rates	0.348	0.217	1
	Alpha	0.207	

For the scenario incorporating exchange rate risk, new correlation coefficients were estimated. As show in Table 20, the multivariate normal copula was determined to be the most appropriate. The Korean Won/U.S. Dollar rate changes exhibit negative correlation with hard red winter wheat futures price changes and PNW to Japan ocean freight rate changes, -.457 and -.464 respectively. Hard red winter wheat futures price changes are positively correlated, .348, to ocean freight rate changes.

Table 20 Scenario #3 Data-Normal Copula Parameters

Multivariate Normal Copula Parameters-South Korea FX (2006-2010) Correlation Matrix				
	KCBT HRWW	PNW 12% Basis	PNW-Japan Ocean	Korean Won/US Dollar
KCBT HRWW	1	0.129	0.348	-0.457
PNW 12% Basis	0.129	1	0.217	-0.103
PNW-Japan Ocean Rates	0.348	0.217	1	-0.464
Korean Won/US Dollar	-0.457	-0.103	-0.464	1

CHAPTER V. RESULTS

This chapter presents the results from the MaR model for each of the flour milling scenarios along with an analysis of different estimation procedures, the base being normal distributions and copulas with the alternate being non-normal distributions and copulas. The results give each representative scenario a quantitative measure of worst probable margins in dollar terms. This provides a benchmark to evaluate the effectiveness of different risk management strategies. Scenario 1 is the North American competitive market scenario. This scenario includes an analysis of fixed and random flour prices. The base estimation procedure for this scenario utilizes normal distributions and copulas, while and alternate estimation procedure utilizes alternative distributions and copulas. Time and confidence level sensitivities are also explored for each. Scenario 2 is the international regulated market scenario. In this scenario, flour prices are assumed to be fixed by the government. Exchange rate risk is not considered in this scenario. Again, different estimation procedures are analyzed as well as different confidence levels. Scenario 3 is the international regulated market with exchange rate risk. Again, flour prices are assumed to be fixed by the government. However, exchange rate risk is included in the analysis. As with the other scenarios, different estimation procedures are analyzed as well as confidence level sensitivities.

The interpretation of the MaR utilized in the analysis can be described as the lowest margin one month forward with a probability specified by the confidence level. So, a MaR of -$1,000,000 at the 90% confidence level means that with 90% probability the lowest margin observed will be -$1,000,000 over the one month time horizon. An implication of this definition is that there exists a 10% probability that the margin will be lower than the MaR result.

North American Competitive Market Scenario

The first scenario analyzed is the North American competitive market scenario with the base procurement and marketing strategy. Also, normal price change distributions and multivariate normal copulas were assumed as the appropriate modeling techniques. Table 21 presents the results.

Table 21 Scenario #1 Flour Fixed Price (2006-2010)-Base Estimation Procedure

Margin-at-Risk ($) Minneapolis Base Procurement and Marketing Strategy- Normal Assumption						
	99% C.L.	**99% Rank**	**95% C.L.**	**95% Rank**	**90% C.L.**	**90% Rank**
Short Cash	-1,525,750	7	-1,010,151	7	-752,771	7
Hedged Futures	-1,016,880	4	-632,042	4	-435,084	4
Basis Contract	-1,076,865	5	-701,038	5	-498,056	5
Forward Contract	-92,508	2	10,551	2	67,027	2
Short Cash & Mill feeds Sold	-1,544,269	8	-1,047,628	8	-775,984	8
Hedged Futures & Mill feeds Sold	-928,120	3	-597,747	3	-405,836	3
Basis Contract & Mill feeds Sold	-1,158,995	6	-750,649	6	-546,903	6
Forward Contract & Mill feeds Sold	249,675	1	249,675	1	249,675	1

The forward contract with mill feeds sold is the best risk management strategy, assuring a positive gross margin from the milling process. Note, there is zero variance of the MaR result for that strategy as all random variables are fixed due to risk management measures taken. The forward contract strategy provides the next best alternative, followed by the hedged futures with mill feeds sold and the hedged futures. Since flour is priced according to a pricing function which incorporates futures price and local basis, a strategy which fixes both the futures and basis provides the best protection for the margin. Also, futures prices are the primary driver of flour prices. If flour prices are already sold, assumed fixed, hedging futures price risk provides an effective first measure.

For the alternate distributional procedure, all variables utilize the Laplace distribution except for mill feeds, which utilizes the error function distribution. These distributions are more leptokurtic than the normal distribution. Also, a student t copula is used. Since there are a limited number of observations, the student t copula exhibits fatter joint distribution tails. If there were more observations, and thus more degrees of freedom, the student t copula would converge to the normal distribution. The procedure results in more negative MaR values due to incorporating distributions with more kurtosis relative the normal distribution, as shown in Table 22. Also, the ranking of the risk management strategies under analysis remained the same as the normal distributional procedure.

Table 22 Scenario #1 Flour Fixed Price (2006-2010)-Alternate Estimation Procedure

Margin-at-Risk ($) MPLS (2006-2010) Base Procurement and Marketing- Alternative Distributions						
	99% C.L.	**99% Rank**	**95% C.L.**	**95% Rank**	**90% C.L.**	**90% Rank**
Short Cash	-1,792,971	7	-830,968	7	-520,995	7
Hedged Futures	-1,088,430	4	-507,887	4	-278,059	4
Basis Contract	-1,276,403	5	-653,242	5	-383,988	5
Forward Contract	-102,202	2	-160	2	55,982	2
Short Cash & Mill feeds Sold	-1,836,583	8	-852,184	8	-548,324	8
Hedged Futures & Mill feeds Sold	-1,006,326	3	-464,398	3	-237,142	3
Basis Contract & Mill feeds Sold	-1,375,867	6	-689,790	6	-425,126	6
Forward Contract & Mill feeds Sold	249,675	1	249,675	1	249,675	1

As Table 23 exhibits, the alternative procurement and marketing scenario produces wholly different rankings of the risk management strategies, due to flour being unsold and thus random. Due to the strong correlation coefficient, .85, between hard red spring wheat futures prices and 13.5% Baker's Standard Patent flour prices, pricing wheat, in the form of forward contracts or hedged futures, while flour is priced is a poor risk management measure. In this scenario, a basis contract is the most appropriate measure. This is due to futures prices being the primary driver of costs in milling.

Table 23 Scenario #1 Flour Random Price (2006-2010)-Base Estimation Procedure

Margin-at-Risk ($) MPLS (2006-2010) Alternate Procurement and Marketing- Normal Assumption						
	99% C.L.	99% Rank	95% C.L.	95% Rank	90% C.L.	90% Rank
Short Cash	-886,602	4	-548,046	3	-374,444	3
Hedged Futures	-1,398,844	8	-895,370	8	-622,411	8
Basis Contract	-471,674	1	-248,401	1	-143,566	1
Forward Contract	-1,101,018	6	-678,356	6	-451,472	6
Short Cash & Mill feeds Sold	-882,090	3	-552,880	4	-385,955	4
Hedged Futures & Mill feeds Sold	-1,295,503	7	-834,004	7	-588,138	7
Basis Contract & Mill feeds Sold	-500,798	2	-289,013	2	-172,879	2
Forward Contract & Mill feeds Sold	-1,032,234	5	-621,063	5	-421,133	5

The alternative distributional procedure, with results presented on Table 24, again utilizes Laplace distributions for all market risk variables except for mill feeds. Also, the student-t copula is utilized as well. As with the flour sold scenario, the rankings of strategies remain the same. However, MaR values are larger. This is again due to distributions, both individual and joint, that exhibit higher levels of kurtosis than the normal distribution.

Table 25 presents the results from the data sample post 2008's period of extreme volatility. Due to the sample period being significantly less volatile, the MaR results are correspondingly much less. The only change between the rankings of strategies is for basis contracts. The standard deviation of the basis is significantly less using this time period for both wheat protein markets. During times of short supplies, the market becomes inverted to service spot market needs and eliminates any incentive to carry inventories. This situation results in basis volatility as the market panic buys to cover its needs. By removing the basis volatility of 2008 caused by historically low stocks, having an unestablished basis becomes a better risk management strategy.

Table 24 Scenario #1 Flour Random Price (2006-2010)-Alternate Estimation Procedure

Margin-at-Risk ($) MPLS (2006-2010) Alternate Procurement and Marketing- Alternate Distributions						
	99% C.L.	**99% Rank**	**95% C.L.**	**95% Rank**	**90% C.L.**	**90% Rank**
Short Cash	-986,561	4	-431,630	4	-241,071	4
Hedged Futures	-1,590,307	8	-795,043	8	-500,955	8
Basis Contract	-645,711	1	-247,828	1	-103,549	1
Forward Contract	-1,420,828	6	-735,247	7	-434,748	6
Short Cash & Mill feeds Sold	-951,469	3	-415,382	3	-220,192	3
Hedged Futures & Mill feeds Sold	-1,462,900	7	-715,733	6	-438,999	7
Basis Contract & Mill feeds Sold	-662,749	2	-253,448	2	-106,661	2
Forward Contract & Mill feeds Sold	-1,367,614	5	-661,088	5	-386,881	5

The same scenario with the non-normal distributional procedure yields the same rankings, as shown by Table 26. Each individual variable utilizes the Laplace distribution except for mill feeds, which utilizes the error function distribution. A multivariate normal copula was selected as the most appropriate. As expected, the MaR values are more negative as the procedure accounts for the kurtosis exhibited in the data and thus fatter tails of the MaR distribution.

Table 25 Scenario #1 Flour Fixed Price (2009-2010)-Base Estimation Procedure

Margin-at-Risk ($) MPLS (2009-2010) Base Procurement and Marketing- Normal Assumption						
	99% C.L.	**99% Rank**	**95% C.L.**	**95% Rank**	**90% C.L.**	**90% Rank**
Short Cash	-649,172	5	-374,841	5	-252,139	5
Hedged Futures	-465,436	4	-239,863	4	-123,225	4
Basis Contract	-709,834	7	-450,673	7	-302,642	7
Forward Contract	-64,493	2	23,465	2	75,659	2
Short Cash & Mill feeds Sold	-701,720	6	-437,215	6	-291,107	6
Hedged Futures & Mill feeds Sold	-396,437	3	-197,032	3	-99,296	3
Basis Contract & Mill feeds Sold	-786,459	8	-486,582	8	-336,958	8
Forward Contract & Mill feeds Sold	249,675	1	249,675	1	249,675	1

Table 26 Scenario #1 Flour Fixed Price (2006-2010)-Alternate Estimation Procedure

Margin-at-Risk ($) MPLS (2009-2010) Base Procurement and Marketing- Alternate Distributions						
	99% C.L.	**99% Rank**	**95% C.L.**	**95% Rank**	**90% C.L.**	**90% Rank**
Short Cash	-694,982	5	-294,218	5	-134,878	5
Hedged Futures	-517,453	4	-194,024	4	-57,903	4
Basis Contract	-872,008	7	-399,441	7	-206,360	7
Forward Contract	-69,652	2	18,361	2	70,588	2
Short Cash & Mill feeds Sold	-755,794	6	-346,576	6	-168,164	6
Hedged Futures & Mill feeds Sold	-479,024	3	-154,050	3	-22,621	3
Basis Contract & Mill feeds Sold	-962,294	8	-441,053	8	-232,145	8
Forward Contract & Mill feeds Sold	249,675	1	249,675	1	249,675	1

International Regulated Market

The international regulated market is more complex than the North American competitive market scenario. This is due to the addition of ocean freight as a variable. Also, flour prices are assumed to be fixed in this scenario, a common practice for governments which import wheat.

Two different distributional procedures were utilized. The first included normal univariate distributions and a normal multivariate copula. The alternate distribution procedure utilized the Laplace distribution for wheat futures prices, the hyperbolic secant distribution for the basis and the extreme value minimum distribution for ocean freight rates. A Clayton multivariate copula was used to construct the multivariate equation. All of the univariate distributions have greater levels of kurtosis than the normal distribution. Also, the Clayton copula imposes greater dependence towards the downside. This results in MaR values that are lower than the base distributional procedure.

Forward contracts with a C&F transportation strategy provides the most protection of the margin followed by forward contracts with a FOB transportation strategy. The C&F strategy, which assumes zero variance of ocean freight rates, improves the MaR compared to the FOB strategy. A FOB strategy contractually obligates the buyer to handle shipping responsibilities, thus taking on freight rate risk. Again, since wheat prices are the primary drivers of procurement costs, eliminating that risk is a beneficial strategy. Hedging futures provides the next most effective risk management strategy. Table 27 presents the results from the normal distributional procedure.

As shown in Table 28, the alternate distributional procedure maintains the rankings of risk management strategies while producing more negative MaR values. This is a product of non-normal individual and joint distributions.

Table 27 Scenario #2 (2006-2010)-Base Estimation Procedure

Margin-at-Risk ($) Korea (2006-2010) No Exchange Rate Risk - Normal Assumption						
	99% C.L.	**99% Rank**	**95% C.L.**	**95% Rank**	**90% C.L.**	**90% Rank**
Short Cash & Free on Board (FOB)	125,555	8	511,205	8	719,679	8
Hedged Futures & Free on Board (FOB)	1,052,473	4	1,187,840	4	1,260,567	4
Basis Contract & Free on Board (FOB)	312,482	5	659,953	5	833,325	5
Forward Contract & Free on Board (FOB)	1,270,458	2	1,341,978	2	1,381,335	2
Short Cash & Cost and Freight (C&F)	241,130	7	592,800	7	779,527	7
Hedged Futures & Cost and Freight (C&F)	1,174,297	3	1,276,038	3	1,330,650	3
Basis Contract & Cost and Freight (C&F)	312,482	5	659,953	5	833,325	5
Forward Contract & Cost and Freight (C&F)	1,519,746	1	1,519,746	1	1,519,746	1

Table 28 Scenario #2 (2006-2010)-Alternate Estimation Procedure

Margin-at-Risk ($) Korea (2006-2010) No Exchange Rate Risk - Alternate Distributions						
	99% C.L.	**99% Rank**	**95% C.L.**	**95% Rank**	**90% C.L.**	**90% Rank**
Short Cash & Free on Board (FOB)	43,029	8	608,618	8	859,524	8
Hedged Futures & Free on Board (FOB)	1,065,799	4	1,222,504	4	1,295,544	4
Basis Contract & Free on Board (FOB)	142,114	5	695,808	5	942,760	5
Forward Contract & Free on Board (FOB)	1,339,489	2	1,377,263	2	1,398,535	2
Short Cash & Cost and Freight (C&F)	106,256	7	644,374	7	894,748	7
Hedged Futures & Cost and Freight (C&F)	1,129,321	3	1,281,803	3	1,348,223	3
Basis Contract & Cost and Freight (C&F)	142,114	5	695,808	5	942,760	5
Forward Contract & Cost and Freight (C&F)	1,519,746	1	1,519,746	1	1,519,746	1

International Regulated Market With Forex Risk

The last scenario is the grain importer in a regulated market with exchange rate risk. The exchange rate risk adds to the variability of output prices, which are assumed to be fixed by the government. However, the model produces results that are counter-intuitive. Table 29 presents MaR values that are significantly more positive than the previous scenario without exchange rate risk. After reviewing the analysis, it can be concluded that the inverse correlations between the South Korea Won/U.S. Dollar exchange rate and the rest of the market risk variables acts as a hedge against risk. This is the apparent reason for the higher forecasted margins at the lower tail percentiles.

In the normal distributional assumption model, forward contracts with FOB transportation provide the best margin followed by forward contracts with C&F transportation. Again, forward contracts are the best wheat procurement strategy followed by a hedged futures strategy.

The alternate distributional scenario produces similar results, as shown in Table 30. The only difference is for the 99% confidence level MaR, the FOB hedged futures strategy is the second best strategy, instead of the C&F forward contract strategy. This is due to the hyperbolic secant distribution selected for the PNW 12% hard red winter wheat basis. The hyperbolic secant distribution is symmetrical but with higher levels of kurtosis relative to the normal. The heavier weighting of tail events changes the MaR distribution at the highest confidence level. Again, as with all of the alternative distributional results, MaR values were more negative than the normality assumption.

Table 29 Scenario #3 (2006-2010)-Base Estimation Procedure

Margin-at-Risk ($) Korea (2006-2010) Exchange Rate Risk- Normal Assumption						
	99% C.L.	99% Rank	95% C.L.	95% Rank	90% C.L.	90% Rank
Short Cash & Free on Board (FOB)	1,632,339	8	1,950,487	8	2,136,694	8
Hedged Futures & Free on Board (FOB)	2,105,392	3	2,318,988	3	2,426,203	3
Basis Contract & Free on Board (FOB)	1,707,604	6	2,012,606	6	2,181,230	6
Forward Contract & Free on Board (FOB)	2,206,091	1	2,378,619	1	2,471,644	1
Short Cash & Cost and Freight (C&F)	1,705,064	7	1,991,460	7	2,167,634	7
Hedged Futures & Cost and Freight (C&F)	2,066,259	4	2,288,163	4	2,407,229	4
Basis Contract & Cost and Freight (C&F)	1,760,517	5	2,047,264	5	2,215,362	5
Forward Contract & Cost and Freight (C&F)	2,133,454	2	2,335,131	2	2,429,770	2

Table 30 Scenario #3 (2006-2010)-Alternate Estimation Procedure

Margin-at-Risk ($) Korea (2006-2010) Exchange Rate Risk- Alternate Distributions						
	99% C.L.	99% Rank	95% C.L.	95% Rank	90% C.L.	90% Rank
Short Cash & Free on Board (FOB)	1,540,733	8	2,026,409	8	2,241,708	8
Hedged Futures & Free on Board (FOB)	2,123,486	2	2,395,895	3	2,511,708	3
Basis Contract & Free on Board (FOB)	1,662,812	5	2,123,684	5	2,319,489	5
Forward Contract & Free on Board (FOB)	2,194,140	1	2,461,180	1	2,565,447	1
Short Cash & Cost and Freight (C&F)	1,627,761	7	2,066,268	7	2,273,466	7
Hedged Futures & Cost and Freight (C&F)	2,072,998	4	2,373,666	4	2,498,814	4
Basis Contract & Cost and Freight (C&F)	1,662,812	5	2,123,684	5	2,319,489	5
Forward Contract & Cost and Freight (C&F)	2,111,515	3	2,412,481	2	2,528,121	2

Summary

Results of the empirical model from each of the risk management and distributional scenarios were presented. As a general rule, if flour prices are fixed, either by selling in advance or government regulation, then forward contracts are the best strategy followed by hedging futures. However, if flour prices are random, the result of unsold flour inventory, forward contracts and hedged futures are not effective due to the strong correlation between flour and wheat futures prices. A basis contract or short cash procurement strategy are more effective in a scenario with random flour prices.

In this analysis, it was found that the shape of the individual and joint distributions greatly impacted the MaR values produced. By utilizing skewed and/or leptokurtic distributions, more extreme events become more probable due to heavier weighting of the distribution's tail. This demonstrates the downfall of the normal distribution. By not properly accounting for tail events, either by alternate distributions or thorough stress testing procedure, a firm exposes itself to an inadequate risk measurement program.

CHAPTER VI. CONCLUSIONS

A myriad of factors have led to the development of persistent commodity market volatility. Effective risk management is of the utmost of importance to firms involved in the agricultural supply chain; whether it is origination, storage, transportation or processing. Market volatility has necessitated the development of increasingly complex risk management instruments, such as over-the-counter derivatives, in an era of historic volatility. Market risk measurement was originally developed by the financial industry to probabilistically estimate risk exposure in dollar terms to facilitate the use of complex financial instruments. This same methodology can be applied to different facets of the agricultural supply chain.

Agricultural processors face rising input costs during periods of market volatility. More importantly, market volatility makes input and output pricing decisions more difficult. Due to fluctuating input and output prices, which may not be moving synchronously, firms are exposed to the risk of poor margins. In the worst case, negative margins caused by poor risk management decisions can deplete a firm's capital. It is important for firms to quantitatively asses risk exposure by employing risk measurement methods.

Value-at-Risk

Value-at-Risk is a common method of measuring market risk. VaR measures a portfolio's possible downside loss over a certain time period in dollar terms. It accomplishes this by estimating the volatilities and correlations of the assets within the portfolio. These inputs are used to generate a distribution of portfolio changes. A specified confidence level is then used to calculate the portfolio's "Value-at-Risk". An important implication of this is that losses outside of the confidence interval occur during "non-normal" market conditions. The benefit of VaR is that a probabilistic risk exposure can be reported to a firm's management in dollar terms. Also, limits to risk exposure at different levels can be used to ensure a company has an adequate liquid capital base to withstand losses.

An important facet of risk measurement is the selection of the method of generating distributions. In financial and agricultural markets, non-normal return distributions are common. Commonly, the normal distribution is assumed due to its computational efficiency. Also, the assumption of normality implies that a portfolio is a linear combination of its assets' returns. Thus, the assumption of normal univariate distributions and linear correlation is problematic. Tail events are a reality and have serious consequences. To account for these, non-normal distributions and copulas can be used to better factor tail events into the risk measure.

Summary of Results

The purpose of this research is to demonstrate how market risk measurement methods can be applied to the agricultural processing margin. Specifically, multiple flour milling scenarios were utilized along with multiple distributional procedures. Different time and confidence level were utilized to demonstrate the importance of the managerial decisions involved with the risk measurement process. The method and results provide an example for processing firms to utilize in their risk management decisions.

Scenario 1 focused on the competitive North American market. An important part of this analysis was the pricing of flour. The analysis exhibited the risk that is involved without "locking in" input and output prices at the same time. Any time left between the pricing of input and output complicates risk management decisions for processors. In the flour sold scenario, fixing futures prices by forward contracting or hedging futures proved to be the best risk minimizing decision. However, in the flour unpriced scenario, leaving price random and locking in the basis proved to be the best risk minimizing decision. Another facet of the analysis was excluding the volatile time period of 2008. By excluding this time period, the risk measure lessons. This reiterates the important of the sampling period used for the estimation of any market risk measure.

In Scenario 2, the analysis focused on the problem of an international flour mill with import requirements. Ocean freight is an added variable caused by the unique nature of an importing miller located in a wheat deficit nation. Exchange rate risk was not considered in this scenario. Another feature of this analysis is that flour prices are assumed to be fixed by the government. Due to this, flour prices are fixed. Again, fixing price by forward contracting or hedging futures proves to be the best risk minimizing decision. Another conclusion is that a FOB contract, a contract in which the seller takes on freight rate risk, minimizes risk compared to the other transportation alternative, a C&F contract in which the buyer takes on freight rate risk.

Scenario 3 is the same as Scenario 2 except with the addition of exchange rate risk. Again, fixing price by forward contracting or hedging futures proved to be the best risk minimizing decision. In this case, a FOB contract minimized risk relative to the C&F

contract. This can be explained by the inverse correlation, -.46, between PNW-Japan ocean freight rates and Korean Won/US Dollar exchange rate risk. Also, MaR values were considerably better than Scenario 2's results. The inverse correlation between Kansas City wheat futures and Korean Won/US Dollar, -.46, explains this result.

The most important conclusion that can be drawn from the results is the importance of selecting appropriate distributions and patterns of dependence. MaR values varied significantly given their distributional procedures. By utilizing non-normal distributions and copulas, tail risk can be better estimated. A risk measure is only as good as the calculation method and assumptions of the model.

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