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# Insuring uncertainty in value-added agriculture: ethanol

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**Insuring uncertainty in value-added agriculture: Ethanol**

by

**Nicholas David Paulson**

A thesis submitted to the graduate faculty  
in partial fulfillment of the requirements for the degree of

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Major: Economics

Program of Study Committee:  
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Ames, Iowa

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This is to certify that the master's thesis of  
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has met the thesis requirements of Iowa State University

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Signatures have been redacted for privacy

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**ABSTRACT**

A wide variety of insurance products are currently available for agricultural producers to insure against yield or price risks in the markets for the raw commodities they produce. Value-added enterprises, such as ethanol production, have become increasingly popular among farmers over the last decade. However, insurance against declines in the value-added portion of their crops is not yet available. This paper outlines the development of an insurance product aimed at corn producers who are members of an ethanol production cooperative. The product mimics the gross margin level of a typical ethanol production facility, and has the potential to provide producers with a new and useful risk management tool to insure against price risks in the markets for corn, distillers dried grains with solubles (DDGS), ethanol, and natural gas. Monte Carlo analysis is used to develop fair premiums at various coverage levels. A historical correlation structure is imposed on the simulated price data, using a method proposed by Iman and Conover which maintains the marginal distributions of the variables. Historical analysis is carried out to examine how the product would have performed had it been offered over the last decade. The product is shown to perform as intended, paying indemnities in years of extreme price volatility.

## INTRODUCTION

### General Introduction

Value-added enterprises, such as ethanol production, have recently gained interest as tools for farmers to create new markets for selling their products. The Renewable Fuels Association (RFA) website reports that, as of February 2004, there were over 80 ethanol production facilities operating, expanding, or under construction in the United States (U.S.). This comprised a total production capacity of over 3.7 billion gallons annually, which was more than a 40 percent increase in capacity from 2001. Almost 90 percent of these ethanol plants use corn as the main feedstock or as a component in a mixed feedstock (i.e. corn-milo mixtures) in the production process, representing almost 98 percent of the annual ethanol production capacity in the U.S. Iowa's production capacity, as of February 2004, stood at roughly 867 million gallons annually, or 23.5 percent of the U.S. annual production capacity (Renewable Fuels Association, 2004).

Roughly half of these production facilities are set up as farmer-owned cooperatives, or limited liability corporations (Renewable Fuels Association, 2004). Some of these farmer-owned facilities require farmers to provide an initial investment to obtain partial ownership in the facility, and then they receive premium payments that are based on plant profitability in addition to what they receive for any grain they market to the facility. The EXOL ethanol production plant located in Albert Lea, MN is an example of one of these types of farmer-owned ethanol plants (EXOL, 2004). The farmer-owned ethanol production facilities account for 40 percent of the total annual production capacity of the U.S. (Renewable Fuels Association, 2004). In some cases, membership "shares" are sold on a per bushel basis

designating a delivery requirement, with premium payments made based on the proportion of total bushels processed that the producer delivers (EXOL, 2004).

According to the United States Department of Agriculture's Risk Management Agency (USDA RMA) website, the vast majority of federally subsidized crop and revenue insurance policies sold in the U.S. are single crop policies that insure against low yields or revenues for each crop grown on the farm. These policies provide price and yield risk insurance for the commodity based on its raw form being sold as the final product. However, there are currently no federally subsidized insurance products available through the USDA RMA that provide coverage for value-added enterprises such as marketing grain used for ethanol production (Risk Management Agency, 2004). Therefore, farmers are not able to implement a complete risk management plan for the portion of their production that is linked to these value-added enterprises.

The purpose of this research was to develop a risk management tool that provides corn producers, who are involved in ethanol production, the ability to insure against poor financial performance of the facility. By insuring against circumstances causing low profits in the ethanol plant, the product will provide value to its owner during periods of low premium payments. The product mimics the gross margin level of a typical ethanol production facility that implements the dry-mill production process using corn as the feedstock. The gross margin, premium, and indemnity levels are calculated on a per bushel basis to enable producers to utilize the product based on how many bushels of corn they intend to market to the ethanol facility over the contract year.

A Monte Carlo analysis, which implements the use of simulated data to examine possible realizations under uncertainty, is used to calculate fair premiums for the product at

various coverage levels. Sensitivity analysis is also performed by calculating fair premium rates under the assumption of higher levels of price volatility. Historical prices are used to examine how the product would have performed had it been offered over the previous decade. The product is shown to perform as intended, paying indemnities to the owner during periods of high price volatility.

### **Thesis Organization**

The remainder of this thesis is organized as follows. Chapter 2 is a brief literature review outlining previous research in related areas using similar methodology. Chapter 3 outlines the methodology used for each component of this research. Chapter 4 reports the results. Finally, Chapter 5 summarizes the conclusions, along with suggestions for future research in related areas. The appendix contains additional data and figures. References are given at the end of this thesis.

## LITERATURE REVIEW

### Ethanol Industry History and Outlook

The use of ethanol, or ethyl alcohol, as a transportation fuel source dates back to the early 1900s when Henry Ford invented the Model T. However, high tax rates and the low cost of petroleum-based gasoline prevented extensive growth in the ethanol industry. Alcohol and gasoline were used as a fuel blend during periods of oil shortages during World War I (WWI) and World War II (WWII), but following WWII oil prices hit an all-time low making ethanol too expensive to even consider as an alternative to petroleum based fuels (Buchheit, 2002 and Energy Information Administration, 2004). It was not until the OPEC oil embargo of the early 1970s that the potential of ethanol was once again investigated. In 1977, the Food and Agricultural Act was passed, which provided loan guarantees for biomass pilot plants and extended funding for USDA research on renewable fuels and fossil fuel alternatives (Energy Information Administration, 2004).

In 1978, the Energy Tax Act was passed giving a four cent per gallon federal excise tax exemption for ethanol blended motor fuels and granted a ten percent energy investment tax credit for biomass-ethanol conversion equipment. Then in 1979 many major oil companies, led by Amoco Oil Company, began to market commercial alcohol blended fuels. By 1980, ethanol production facilities in the U.S. were producing 175 million gallons of ethanol annually. Between 1980 and 1985, additional tax reforms and environmental legislation increased the excise tax redemption to six cents per gallon and created a new schedule of income tax credits for fuel blenders. The number of ethanol plants reached 163 in 1985 with a production level of 610 million gallons, but only half of the plants existing at

that time were operating due to bad engineering and poor business decisions (Energy Information Administration, 2004).

In 1988 ethanol began to be used as a fuel oxygenate as the city of Denver, Colorado, mandated oxygenated fuels for winter use to control for carbon monoxide emissions. The Clean Air Act Amendments of 1990 mandated oxygenated fuel use in regions all over the country, as the ethanol industry began to shift towards the use of natural gas rather than coal as well as other cost reducing technologies. In 1994, the Environmental Protection Agency (EPA) imposed the Renewable Oxygen Standard (ROS) which required that 30 percent of fuel oxygenates be produced from renewable sources. The ROS was later ruled an unconstitutional constraint to commerce, but it was considered one of the biggest contributing factors to the boon of the corn-ethanol industry (Energy Information Administration, 2004).

Annual ethanol production in the U.S. grew to 1.6 billion gallons in 1995. Volatile corn markets in the following year caused ethanol production to fall to 1.1 billion gallons in 1996, but production levels have climbed steadily since then to over 2.8 billion gallons in 2003. The current ethanol federal excise tax exemption stands at 5.2 cents per gallon for ten percent ethanol blends and will be cut to 5.1 cents per gallon in 2005. The tax exemption is scheduled to expire on December 31<sup>st</sup>, 2006 (Renewable Fuels Association, 2004).

The amount of corn utilized for ethanol production has seen a steady increase from 70 million bushels in 1980 to over one billion bushels, or ten percent of U.S. corn production, in 2003. Ethanol production is projected to use two billion bushels of corn annually by the year 2012 to produce over five billion gallons of ethanol (Renewable Fuels Association, 2004).

It is estimated that a 40 million gallon per year plant provides a \$142 million one-time boost to a local economy while also expanding the local economic base by \$110.2 million per year through \$56 million of annual direct spending. Such a plant is also estimated to create 41 full-time jobs at the plant and over 600 jobs throughout the local economy. Local corn prices can be expected to raise five to ten cents per bushel, helping to increase farm incomes while also boosting state and local sales tax receipts by an average of \$1.2 million each year. The typical plant is also estimated to provide an average ten-year return of 13.3 percent to the plant's investors (Kapell and Urbanchuck, 2002).

The continued growth of the ethanol industry in the U.S. hinges on multiple factors. Demand driven factors include the use of ethanol to replace other types of fuel additives such as Methyl Tertiary Butyl Ether (MTBE) (DiPardo, 2002). While MTBE helps to improve engine efficiency and reduce emissions, it has also been linked to contamination of drinking water supplies in regions all over the country. The direct health threats of MTBE are currently unknown but its use is currently being phased out in many areas, including the state of California, leading to increased demand in new and larger markets for ethanol as a fuel additive (Environmental Protection Agency, 2004 and DiPardo, 2002).

Government policy is another factor that will affect future growth in the ethanol industry. At current prices, ethanol is still dominated by petroleum based energy sources. However, with subsidy programs sponsored by the federal government and environmental regulations on emissions standards, ethanol has been able to enter and compete in major energy markets (Renewable Fuels Association, 2004). With passage of the American Jobs Creation Act of 2004 in October 2004, the government has extended the federal support through 2010. The new bill effectively removes the excise tax exemption of 5.1 cents per

gallon on alcohol fuels, while creating a tax credit of 51 cents per each gallon of alcohol fuel used by fuel suppliers to create petroleum-alcohol fuel blends (Harl and McEowen, 2004).

Another area of concern for the ethanol industry is the future projections for corn supply. Wisner and Baumel (2004) report that the current growth rate of corn utilization is larger than the growth rate of domestic production. They attribute much of the increased demand to ethanol production growth and possible excess demand from Chinese markets. In fact, record crops in 2003 and another record crop projected for 2004 were unable to meet market requirements in either year. If corn production continues to fail to meet market requirements, there may be large price implications as the price of corn increases (Wisner and Baumel, 2004).

### **Ethanol Production Process**

The dry mill process of producing ethanol, using corn as a feedstock, is a mature technology that is not likely to see significant cost reductions or increases in production efficiency (DiPardo, 2002). According to the Iowa Value Added Resource Manual and discussions with the Iowa Independent Renewable Fuels Association (IRFA), the dry-mill ethanol production process converts corn into ethanol according to the following input-output relationship:

Inputs:	1 bushel (bu.) of Corn
	0.165 million British thermal units (mmBtu) of Natural Gas
Outputs:	2.7 gallons of Ethanol
	17 lbs. (0.0085 tons) of Distillers Dried Grains and Solubles (DDGS)

While the input-output ratio is fixed across operations, fixed and overhead cost structures will most definitely differ between plants.



### **Ethanol and DDGS Markets**

As of June 2002, there were no futures contracts traded on any of the major futures exchanges in the U.S. for ethanol or DDGS (Chicago Board of Trade, 2004, New York Mercantile Exchange, 2004 and New York Board of Trade, 2004). Prices for both of these commodities are determined on regional cash markets. In May 2004, the New York Board of Trade (NYBOT) introduced both futures and options contracts for ethanol derived from sugar (New York Board of Trade, 2004). The Chicago Board of Trade (CBOT) is planning on introducing an ethanol futures contract for ethanol derived from corn sometime in 2004 (Chicago Board of Trade, 2004).

Ethanol is used mainly as a fuel additive in unleaded gasoline to improve emissions and reduce the dependence on non-renewable fossil fuels (Renewable Fuels Association, 2004). For ethanol to succeed in this market, the cost, or competitive price, of ethanol must be close to the wholesale price of gasoline. Therefore, historic ethanol prices should exhibit fairly high correlation with historic unleaded gasoline prices (DiPardo, 2002).

DDGS is a type of feed ration additive used mainly in the dairy and beef industries. DDGS has also seen recent use in feeds in both poultry and swine industries. Corn and soymeal are two main substitutes to DDGS as a ration in livestock feed (Renewable Fuels Association, 2004).

### **Value-Added Cooperatives**

Value-added cooperatives, also known as new generation cooperatives, are organized in a different manner than the traditional agricultural cooperative. Farmers are required to make larger financial commitments with the possibility of higher returns, while also meeting

quality and delivery requirements for the specific commodity (National Cooperative Business Association, 2004).

Value-added cooperatives major focus is in value-added processing, whereas the traditional agricultural cooperative focuses mainly on the marketing of the commodity held by the member-owners (Kotov, 1999). These new generation cooperatives typically have some form of democratic control through a one-member, one-vote policy. A board of directors is also typically elected by the membership. Excess earnings are typically distributed to the members as dividends based on proportional ownership in the cooperative (Cropp, 1996).

An Illinois Institute for Rural Affairs survey found that the main reasons for starting a value-added cooperative are to capture more of the added value from crops and low commodity prices. Agriculture has shifted from relatively small and diversified family farms to fewer and larger specialized operations. Farmers operating individually have difficulty expanding their operations to the required scale to be able to become involved in value-added processing. By pooling resources, value-added cooperatives allow small farmers to benefit from the added value of processing such as ethanol production (Waner, 1999).

Legislation has been created to assist new generation ethanol cooperatives through income tax credits. Currently, small cooperatives producing less than 30 million gallons of ethanol a year are eligible for a 10 cent per gallon income tax credit for up to 15 million gallons. This legislation provides farmers with the ability to form ethanol cooperatives and compete with the larger private facilities built by companies such as Archer Daniels Midland and Cargill, Inc. Current legislation facing the U.S. Senate Finance Committee hopes to expand this tax credit to plants producing up to 60 million gallons of ethanol per year while

allowing the tax credit to be passed through to the members themselves. The purpose of these changes is to encourage the creation of farmer-owned cooperatives given the anticipated growth in ethanol production over the next decade (National Cooperative Business Association, 2004).

### **Federally Subsidized Agricultural Insurance Products**

There are currently a wide variety of federally supported risk management tools available to farmers through the USDA RMA. These insurance products insure both price and yield risk by guaranteeing both yield and revenue levels to producers (Risk Management Agency, 2004). Goodwin and Kastens (1993) conducted a survey of Kansas farmers and found that 67 percent stated that commodity prices were their main source of risk, followed by yields and then input prices.

Yield based insurance policies include Actual Production History (APH) policies that provide yield and price guarantees based on the farmer's individual historic yield levels and current prices respectively. The Group Risk Plan (GRP) policy guarantees average yields at a county level based on National Agricultural Statistics Service (NASS) yield projections (Risk Management Agency, 2004).

Revenue based plans include the Group Risk Income Plan (GRIP) policy, which guarantees an average farm revenue for a certain crop on a county level similar to GRP. The Adjusted Gross Revenue (AGR) policy provides a revenue guarantee for the entire farm rather than an individual crop using the individual farmer's historic tax schedules. Crop Revenue Coverage (CRC) provides revenue protection on a single crop based on yield or price decline from initial projections. The Income Protection (IP) policy is similar to CRC, protecting gross income for a specific crop. Revenue Assurance (RA) is available to

guarantee a target revenue based on the farmer's expected revenue (Risk Management Agency, 2004).

All crop policy availability and applicability differ by region and producer and are offered at various coverage levels. Most policies are also offered for a variety of crops and can also include optional catastrophic coverage policy endorsements for excessive crop losses. However, none of the products currently offered through the USDA RMA insure the value-added nature of a crop. Rather they insure price or yield risk only for the commodity in its raw form (Risk Management Agency, 2004).

### **Insurance Contract Specification and Rate Determination**

Hart, Babcock, and Hayes (2001) developed two new types of livestock revenue insurance products for cattle and hog producers using Monte Carlo analysis, effectively insuring producer price risk in livestock and feed price markets. They structured the product as an *Asian Basket Option*, where the payout at maturity equals the difference (if positive) between the value of an asset portfolio and a set strike value. They imposed a historical correlation structure to Monte Carlo simulations of monthly price distributions for livestock and feed prices. They calculated premium rates under the assumptions of lognormally distributed prices as well as under the assumption that prices follow an inverse gamma distribution. They also conducted welfare analysis to compare the welfare gains of revenue insurance relative to the asset portfolios they replicate that are attainable through appropriate futures and options trading transactions. They valued the product based on deviations from predicted price levels in the relevant markets, taking the value of the option as the fair insurance premium. Predicted prices were taken as the average over the first 5 trading days in March for the relevant contract, whereas the actual price used for contract settlement is

taken as the average settlement price over the last 10 trading days in each contract's settlement month. The volatilities used to generate the simulated price distributions were taken as the implied volatilities calculated from at-the-money options in the relevant options markets. Additionally, their product was based entirely on futures market prices to minimize the problem of moral hazard.

### **Distribution of Prices**

Pope and Just (2002) discuss the empirical evidence both in favor of and questioning the assumption of lognormally distributed prices. They discuss the historical widespread acceptance of the assumption of lognormality and the use of option pricing models to rate various types of revenue insurance products. However, they discuss the fact that empirical evidence tends to suggest that modeling prices as lognormal tends to assign lower probabilities to the tails of the distribution than data suggests, a phenomenon often referred to as "leptokurtoticity." Empirical studies done by Black (1975), and Fama (1965), have also shown that actual price behavior may be inconsistent with lognormality.

Sherrick et. al (1996) test the validity of the lognormality assumption with specification tests using soybean option price data. They find that for contracts closer to maturity, the Burr III distribution provides a more accurate representation of the distribution of observed prices compared to the lognormal distribution. The Burr III distribution is represented by the following probability density function (pdf):

$$f(P; \alpha, \gamma, \tau) = \frac{\alpha \gamma P^{\alpha \gamma - 1} (\tau^\alpha + P^\alpha) - \alpha \gamma P^{\alpha(\gamma - 1)}}{(\tau^\alpha + P^\alpha)^{\gamma + 1}}$$

where  $P$  is the random commodity price and  $\alpha$ ,  $\gamma$ , and  $\tau$  are parameters which specify the moments and shape of the distribution. Buschena and Ziegler (1999) also consider different

parametric specifications in modeling price volatility for corn and soybean revenue insurance contracts. They conclude that deviations from lognormality commonly occur close to option expiration, but that the assumption of lognormality is a more accurate approximation to quantify price risk further from contract maturity.

Ritchey (1990), and Melick and Thomas (1997) examined the use of combinations or mixtures of pure distributions for option pricing. They find that using mixtures of normal and lognormal distributions provides more flexibility in obtaining the level of variability in skewness and kurtosis observed in actual price data compared to assuming a simple lognormal distribution. These mixed distributions are typically weighted sums of standard distributions such as the normal and lognormal distributions. By altering the values of the weights in the sum, they were able to achieve extensive flexibility in defining the shape of the mixed distribution.

The lognormal distribution, like the normal distribution, can be characterized by its first two central moments, the mean and variance. A lognormally distributed random variable,  $P$ , can be denoted by the following pdf:

$$f(P; \mu, \sigma) = \frac{1}{P\sigma\sqrt{2\pi}} e^{-\frac{(\ln(P)-\mu)^2}{2\sigma^2}}$$

where:

$$\theta = E[P] = e^{\mu + \frac{\sigma^2}{2}}$$

$$\lambda^2 = Var[P] = e^{2\mu + \sigma^2} (e^{\sigma^2} - 1)$$

If a random variable  $P$  is distributed lognormally then the natural log of  $P$ ,  $\ln(P)$ , is distributed normally denoted by the following pdf:

$$f(\ln P) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$$

where:

$$\mu = E[\ln P] = \ln(\theta^2) - \frac{1}{2} \ln(\theta^2 + \lambda^2)$$

$$\sigma^2 = \text{Var}[\ln P] = \ln\left(1 + \frac{\lambda^2}{\theta^2}\right)$$

Given a desired mean,  $\theta$ , and volatility,  $\sigma$ , one can easily calculate the specific values of  $\lambda$  and  $\mu$  needed to specify a normal distribution of random variables where the exponential of these prices are distributed lognormally (Greene, 2003).

There is an issue that the sum of lognormal random variables is not lognormally distributed. In fact the sum, or average, of lognormal random variables has no closed-form probability density function. Two analytical approximations have been employed in recent literature, using either a lognormal or inverse gamma distribution to represent the required distribution. Turnbull and Wakeman (1991), and Levy (1992) have supported the use of a lognormal distribution as a good approximation. However, Levy (1997) showed that the lognormal approximation does not fare as well as volatilities increase. A more detailed discussion of normally and lognormally distributed random variables can be found in Greene (2003), Woolridge (2003), or Miller and Miller (1999).

### **Black's Option Pricing Model and Implied Volatilities**

Black's option pricing model for European futures uses an asset's volatility and current price along with the given option's strike price to determine the no-arbitrage price of the option (Kolb, 2003). Black's European call option pricing formula<sup>1</sup> is represented by the following formula:

$$c_t = e^{-r(\Delta t)} (F_t N(d_1) - XN(d_2))$$

---

<sup>1</sup> The notation used here follows Kolb (2003). Kolb (2003) also provides a formula for European put options consistent with the Black model based on put-call parity.

where:

$N(\cdot)$  = cumulative normal distribution function

$$d_1 = \frac{\ln\left(\frac{S_t}{X}\right) + (0.5\sigma^2)\Delta t}{\sigma\sqrt{\Delta t}}$$

$$d_2 = d_1 - \sigma\sqrt{\Delta t}$$

$F_t$  = asset price at time t

$X$  = option strike price

$\sigma$  = annualized volatility of the asset

$r$  = risk-free rate used for discounting

$\Delta t$  = time to maturity for the option

The model can also be inverted to use the asset price, strike price, and option price to calculate what is known as the implied volatility of the asset (Kolb, 2003). This can be interpreted as the volatility that is implicit in, or implied by, the asset market given all available information at the current time.

Kolb (2003) and Campbell, Lo, and MacKinlay (1997) discuss the comparisons between implied volatility measures to those calculated with historical data. Some investment professionals argue that implied volatility measures are better estimates of true volatilities since they are “forward looking” in that they embody all investor expectations of how the given asset will perform given current market conditions. However, it is also argued that these implied measures of volatility are restricted directly to parametric specifications within a pricing model (i.e. Black’s model) (Kolb, 2003).

The main advantage of using historical measures of volatility is that actual data is used to compute the volatility. However using past information to project the future behavior of an asset violates the theory of the random-walk behavior of stock prices (Campbell, Lo, and MacKinlay, 1997). Also there is a problem in determining how much historical data to use. While using larger time series of data may provide a more reliable measure, the estimate is based on data that may not be relevant to the asset’s performance over the time period of



interest (Kolb, 2003). For example, using a larger time series may underestimate the true volatility at a given time if estimated after a market crash or boom. Of course using a very current, but small data set does solve the problem of incorporating the most relevant market data, but also lowers the reliability of the estimate due to the small number of observations (Kolb, 2003).

Use of the implied volatility measure computed from the Black model assumes that all of the assumptions and restrictions of the model itself hold. The assumptions of the Black model are that 1) asset prices adjust to prevent arbitrage, 2) stock prices change in a continuous manner over time, and 3) asset returns follow a lognormal distribution (Kolb, 2003). Kolb (2003) and Campbell, Lo, and MacKinlay (1997) provide a more detailed discussion of the theory and implications of Black's option pricing model for futures.

### **Derivative Pricing with Monte Carlo Simulations**

The use of Monte Carlo analysis is popular because of its tractability in various settings compared to other pricing methods such as dynamic-hedging approaches or risk-neutral methods (Campbell, Lo, and MacKinlay, 1997). These alternative pricing methods, as well as applications, are discussed in more detail in Campbell, Lo, and MacKinlay (1997). The methodology of Monte Carlo analysis is to simulate many sample paths of an asset value  $P(t)$ . The asset value is calculated for each sample path, and the current asset value is taken to be the average of these simulated values (Campbell, Lo, and MacKinlay, 1997).

### **Imposing Price Correlations**

To use Monte Carlo simulations to price the product, the correlation between different commodity prices must be captured to develop a set of realistic simulations. Simply assuming independence and then simulating price draws under this assumption does not

capture the real-world interaction between prices in related markets. Pope and Just (2002) discuss three different methods for drawing correlated random variables that come from different marginal distributions.

One approach, which was developed by Johnson and Tenenbein (1981), involves a transformation where functions of uncorrelated random variables are combined, forming a linear combination which yields bivariate distributions embodying the desired degree of correlation. This approach is known as the “weighted-linear combination” approach, where the weights are determined by the degree of correlation between the variables and the distribution used for the transformation. The procedure is analogous to taking random draws from a known distribution and then constructing a linear combination of the draws to yield variables with a known correlation structure. These variables are then transformed into uniform random deviates using the cumulative distribution function from which the draws were taken, and then using the inverse distribution function of the desired marginal distribution to transform the deviates into random draws from the desired marginal (Johnson and Tenenbein, 1981). Johnson and Tenenbein’s method is limited to the bivariate case.

The second method is one which was developed by Fackler (1991), as an extension to Johnson and Tenenbein’s method, for multivariate applications. One disadvantage to Fackler’s method is that the transformations do not necessarily preserve the correlation structure if measured using the simple correlation, or the Pearson correlation coefficient. Spearman’s correlation coefficient, or rank correlation, is preserved through the transformations in Fackler’s method (Pope and Just, 2002).

The third family of methods used in the insurance literature involves the use of copulas. A copula is a function that relates marginal distributions to a joint distribution

function (Pope and Just, 2002). Copulas can be identified from sample data, as outlined by Frees and Valdez (1998). Copulas representing true joint distributions can only be approximated and thus face many limitations. They are parametric in nature leading to sensitivity of parametric misspecification, and also possible bias from approximation errors (Pope and Just, 2002).

Another method for imposing a desired correlation structure to data was first proposed by Iman and Conover (1982). The procedure is open ended, can be implemented using commercial spreadsheet software, and can be imposed on any combination of densities. The original data is manipulated in that the original price draws are resorted. Thus, the technique preserves the original marginal distributional structure of each data series while changing the relationships among the series.

The Iman and Conover procedure has four attractive properties. First, the procedure works well with any distribution function. Most of the previously discussed correlation techniques are directed at standard distribution functions and cannot be used with other distribution functions. Second, the mathematics behind the procedure is not extremely complex. Cholesky factorization and inversion of matrices are the most exotic steps in the procedure. Third, the procedure can be used under any sampling scheme. Fourth, the marginal distributions of interest are maintained throughout the procedure in that the moments of the marginal distributions are not affected by the procedure (Iman and Conover, 1982).

The procedure is based on rank correlations. The rank correlation ( $r_s$ ), also known as Spearman's rho, for a given set of paired data  $(x_i, y_i)$  is calculated by ranking the  $x$ 's and  $y$ 's

among themselves, from high to low (or low to high), and then substituting into the following formula:

$$r_s(x, y) = 1 - \frac{6 * \sum_{i=1}^n d_i^2}{n(n-1)^2}$$

where  $d_i$  denotes the difference between the ranks assigned to  $x_i$  and  $y_i$  and  $n$  is the sample size (Miller and Miller, 1999). Iman and Conover (1982) point out that raw correlation numbers can be misleading when the underlying data is non-normal or contains outliers, which is why the rank correlations are used rather than the simple correlation measure.

The theoretical basis for the procedure is that given a random matrix  $A$  whose columns are assumed to have a correlation matrix  $I$  (the identity matrix) and a desired correlation matrix  $B$ , there exists a transformation matrix  $C$  such that the columns of  $AC'$  (where  $C'$  is the transpose of  $C$ ) have a positive definite correlation matrix  $B$ . Since  $B$  is positive definite and symmetric, there exists a lower triangular matrix (the transformation matrix)  $C$  such that  $B = CC'$  (Iman and Conover, 1982).

Let  $X$  be an  $N \times K$  matrix where each column contains random draws from a specific marginal distribution,  $N$  is the sample size, and  $K$  is the number of variables. Let  $R$  be a matrix, of the same dimensionality of  $X$ , containing what Iman and Conover refer to as "scores." Iman and Conover suggest using ranks, random normal deviates, or van der Waerden scores ( $\Phi^{-1}(i / N+1)$ ) where  $\Phi^{-1}$  is the inverse of the standard normal distribution function,  $N$  is the number of draws, and  $i = 1, \dots, N$ ) as possible scores. Furthermore, the correlation matrix for the columns of  $R$  is assumed to be equal to  $I$  (the identity matrix), meaning the elements of  $R$  are uncorrelated (Iman and Conover, 1982).

Define  $T$  to be the desired rank correlation matrix for a transformation (resorting) of  $X$ . Given  $T$  is positive definite and symmetric it may be written as  $T = PP'$ , where  $P'$  is a lower triangular matrix.  $P$ , the transformation matrix, can be found using Cholesky factorization. The transformed matrix of scores,  $R^* = RP'$ , has a rank correlation matrix  $M$  which is approximately equal to the target rank correlation matrix  $T$ . By rearranging the columns of  $X$  into the same ranking as  $R^*$ , the transformed  $X$  matrix has a rank correlation matrix equal to  $M$ , which is very close to the target correlation matrix  $T$  (Iman and Conover, 1982).

Some of the deviation of  $M$  from  $T$  is due to correlation among the columns of  $R$ , meaning the assumption of the correlation matrix for the columns of  $R$  to be equal to  $I$  does not hold. Iman and Conover propose a variance reduction procedure to minimize the deviation of  $M$  from  $T$ . A matrix  $S$  is found, such that  $SDS' = T$ , where  $D$  is the actual correlation matrix associated with the columns of  $R$ . Cholesky factorization can then be used to find a lower triangular matrix  $Q$ , where  $D = QQ'$ . Therefore  $SQQ'S' = PP'$ . Obviously, one possible solution is that  $S = PQ^{-1}$ , where  $Q^{-1}$  denotes the inverse matrix of  $Q$ . Then the transformed matrix  $R^*_B = RS'$  will have a correlation matrix exactly equal to  $T$ . Let the rank correlation matrix of  $R^*_B$  be equal to  $M_B$ . Comparing  $M_B$  to  $M$  and  $T$ , it is shown that  $M_B$  is a more accurate approximation to the target rank correlation matrix  $T$  (Iman and Conover, 1982).

For their analysis, Iman and Conover used van der Waerden scores in the score matrix. Hart, Hayes, and Babcock (2003) apply the Iman and Conover method in rate determination for whole farm revenue assurance. They show significant reductions in cost

can be achieved through whole farm revenue policies as compared to insuring each farm enterprise individually.

## METHODOLOGY

### Contract Details

The contract was structured on an annual basis running from April to March to align the signup period with the signup periods for many other crop insurance products available to agricultural producers through RMA. At signup, producers will need to provide information on the total number of bushels that will be marketed (or the ownership share in the facility expressed in bushels) to the ethanol facility during the contract year.

This product insures price risks in two energy markets (ethanol and natural gas), one raw agricultural commodity market (corn), and a by-product feed market (DDGS). The majority of the value-added ethanol cooperatives have annual delivery requirements for each member based on their proportion of ownership in the facility (National Cooperative Business Association, 2004). However, only producers who are eligible to insure corn under a crop or revenue product will be eligible to purchase the product, therefore production risk is not considered in the development of this product.

Predicted commodity price levels and the dry-mill fixed proportions technology determine the guaranteed level of gross margin according to the following formula:

$$MarGuar = \left( \frac{1}{12} \right) \left[ 2.7 * \sum_{t=1}^{12} ETHP_t + 0.0085 * \sum_{t=1}^{12} DDGP_t - \sum_{t=1}^{12} CORNP_t - 0.165 * \sum_{t=1}^{12} NGP_t \right] \quad (1)$$

where:

- $MarGuar$  = guaranteed level of average gross margin (\$/bu.)
- $ETHP_t$  = projected ethanol price in month t (\$/gallon)
- $DDGP_t$  = projected DDGS price in month t (\$/ton)
- $CORNP_t$  = projected corn price in month t (\$/bu.)
- $NGP_t$  = projected natural gas price in month t (\$/mmBtu)

This formulation assumes equal marketings to the facility over the contract year. However, the product could also be formulated for producers who deliver their corn to the facility on a

different delivery schedule by appropriately “weighting” the monthly commodity prices in the formulation. The results reported in this study were all based on margin guarantees and actual gross margins assuming equal marketings by the producer throughout the year.

### **Predicting Prices and Price Proxies**

To be able to formulate the product per the preceding structure, predicted price levels are needed for ethanol, corn, natural gas, and DDGS. Predicting corn and natural gas prices can be done directly using the futures markets for these commodities. However, there were no futures markets for ethanol or DDGS prices at the time this research was conducted. Therefore, pricing proxies were developed for these two commodities to be able to formulate the product. The introduction of futures markets for ethanol on the NYBOT and CBOT in 2004 provides the future potential for more accurately pricing a product of this nature. The popularity and trading volume in these markets will determine how useful they could be to more accurately price an insurance product for corn growers who are involved with ethanol production.

DDGS is a type of feed ration additive used mainly in the dairy and poultry industries. Corn and soymeal are two main substitutes to DDGS as a ration in livestock feed which have existing futures markets. Using a monthly average DDGS price data series from Lawrenceburgh, IN (Economic Research Service, 1994-2003) and average futures settlement prices for corn and soymeal over the same time period, the simple correlations between DDGS, corn, and soymeal were calculated. The correlation between DDGS and corn prices was found to be 0.775, while the correlation between DDGS and soymeal prices was found to be 0.7. Since corn and DDGS exhibited a higher (marginally) correlation, corn was chosen to develop a price proxy for



DDGS. The data sets for DDGS and corn prices are plotted in Figure 1. The DDGS price data were regressed against the corn futures data, using the method of ordinary least squares (OLS),<sup>2</sup> to estimate the following model:

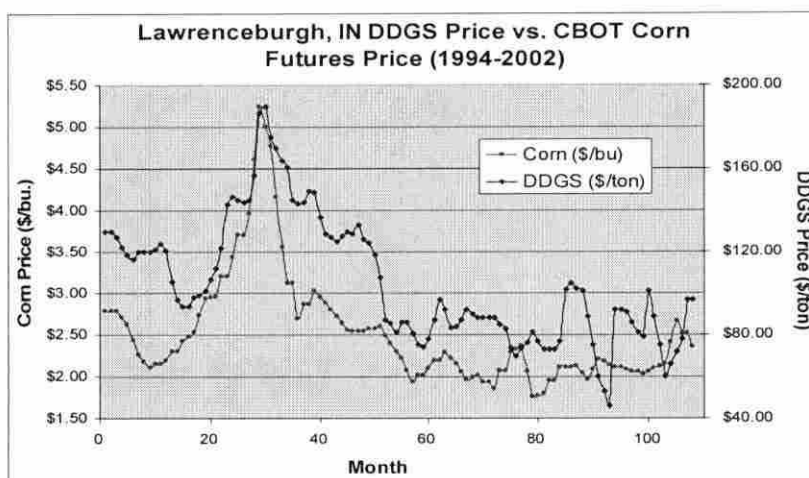
$$DDGP_t = \alpha + \beta * CORNP_t + \varepsilon_t \quad (D)$$

where:

$DDGP_t$  = DDGS price in month  $t$  (\$/ton)

$CORNP_t$  = corn price in month  $t$  (\$/bu.)

$\varepsilon_t$  = zero-mean, homoskedastic error-term



**Figure 1: DDGS Price vs. Corn Price, monthly averages**

Ethanol is used mainly as a fuel additive in unleaded gasoline to improve emissions and reduce the dependence on non-renewable fossil fuels. Therefore, there is a fairly strong relationship between ethanol and unleaded gasoline prices. The simple correlation between unleaded gasoline and ethanol was found to be 0.64. This was calculated using an average monthly price series of ethanol rack prices from Omaha, Nebraska (Nebraska Energy Office, 2004), and unleaded gasoline futures settlement prices averaged over the settlement month. The data sets for ethanol and unleaded gasoline prices are plotted in Figure 2. The ethanol

<sup>2</sup> OLS is the estimation method used for all regression analysis in this paper.

price series was regressed against the unleaded gasoline futures price series to estimate the following model:

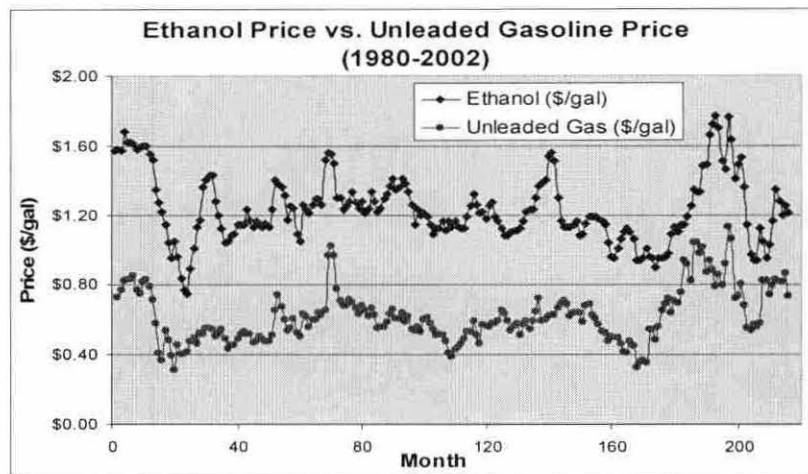
$$ETHP_t = \alpha + \beta * UNLP_t + \varepsilon_t \quad (E)$$

where:

$ETHP_t$  = ethanol price in month  $t$  (\$/gallon)

$UNLP_t$  = unleaded gasoline price in month  $t$  (\$/gallon)

$\varepsilon_t$  = zero-mean, homoskedastic error-term



**Figure 2: Ethanol Price vs. Unleaded Gasoline Price, monthly averages**

The Root Mean Square Error (RMSE) was calculated for the pricing models to compare their predictive accuracy to that of the accuracy level in futures markets. The RMSE measures for ethanol and DDGS reflect the level of accuracy of pricing models D and E. The RMSE was calculated in each commodity's typical measure of price per unit as well as on a percentage basis for comparison across markets. The base price level used in calculating the percentage based RMSE was taken as the average over the predicted and actual price levels for each respective commodity.

Projected prices are based on futures settlement prices<sup>3</sup> for corn from the CBOT, and unleaded gasoline and natural gas futures prices from the New York Mercantile Exchange (NYMEX). The projected prices for all commodities will be taken as the average of the relevant futures contract settlement price over the first 5 trading days in March of the contract year. For example, the projected price for corn in December of the contract year will be taken as the average of the futures quotes for the December corn contract over the first 5 trading days in March of the contract year. Non-contract month prices for corn are determined by linear interpolation between the previous and nearby contract months projected prices. The projected price levels for gasoline and corn are used with pricing models D and E to calculate price predictions for ethanol and DDGS.

Historically, unleaded gasoline futures have not always been traded out a full year when analyzing March future quotes (Barchart.com, 2002). In years where futures quotes were not traded a full year out, the crude oil market was used to create synthetic unleaded gasoline predictions. Oil futures have historically been traded over a full year out, with the historical monthly correlation between unleaded gasoline and crude oil futures prices averaging 0.98. The synthetic unleaded prices are calculated by taking the percentage change in the predicted crude oil price from one contract month to the next, and extrapolating that change onto the predicted price for gasoline. For example, in March of 1997 the unleaded gasoline futures market was trading out through the December 1997 contract. The predicted price for unleaded gasoline for the January 1998 contract was calculated by extrapolating the percentage change in price from the December 1997 to the January 1998 crude oil contract predictions onto the predicted unleaded price for December 1997.

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<sup>3</sup> All futures price data was obtained from [www.barchart.com](http://www.barchart.com)

### Time Series Issues

A common problem in using regression analysis with time series data is the presence of serial correlation (i.e.  $Corr[\varepsilon_t, \varepsilon_{t+h}] \neq 0$ , for  $h \neq 0$ ). According to Woolridge (2003), under the assumptions of the linear relationships for the price series and a zero-mean error term, the OLS regression coefficient estimates are unbiased (i.e.  $E[\hat{\beta}] = \beta$ ). However with the presence of serial correlation, the usual standard errors and t-statistics are not valid. The presence of serial correlation is very common in regression analysis with time series data. Serial correlation of order  $h$  is defined as the correlation of error terms separated by  $h$  time periods. It is often assumed that  $\lim_{h \rightarrow \infty} Corr[\varepsilon_t, \varepsilon_{t+h}] \rightarrow 0$ , so it is common to test for the presence of serial correlation of order one and generalize the level of serial correlation of higher orders. Woolridge (2003) outlines the following test for serial correlation of order one. The residuals from the serially correlated regression model (in this case model D or E) are regressed on their own one-period lagged values:

$$\hat{\varepsilon}_t = \rho \hat{\varepsilon}_{t-1} + \mu_t \quad (2)$$

Then the standard t-statistic for the coefficient estimate  $\hat{\rho}$  is used to test the null hypothesis  $H_0: \rho = 0$  versus the alternative hypothesis  $H_A: \rho \neq 0$  at a given significance level (usually five percent). Both regression models, D and E, were tested for 1<sup>st</sup> order serial correlation at five percent significance.

One of the simplest and most common transformations used is first differencing. Each price series is transformed by taking the difference between the current period's observation and the previous period's observation. While differencing effectively removes

most of the serial correlation, it also results in the loss of one degree of freedom since the first data point in the series cannot be differenced (Woolridge, 2003).

After testing for serial correlation in models D and E, and finding significant evidence of 1<sup>st</sup> order serial correlation, all of the price series were difference and used to estimate the following regression models for DDGS and ethanol prices:

$$\Delta DDGP_t = \beta * \Delta CORNP_t + \varepsilon_t \quad (\Delta D)$$

$$\Delta ETHP_t = \beta * \Delta UNLP_t + \varepsilon_t \quad (\Delta E)$$

where:

- $\Delta DDGP_t$  = change in DDGS price in month  $t$  (\$/ton)
- $\Delta CORNP_t$  = change in corn price in month  $t$  (\$/bu.)
- $\Delta ETHP_t$  = change in ethanol price in month  $t$  (\$/gallon)
- $\Delta UNLP_t$  = change in unleaded gasoline futures price in month  $t$  (\$/gallon)
- $\varepsilon_t$  = zero-mean, homoskedastic error-term

It should be noted that models  $\Delta D$  and  $\Delta E$  have different interpretations than models D and E. Models  $\Delta D$  and  $\Delta E$  predict the change in the value of the dependent variable given a change in the independent variable. Models D and E can be used to directly predict prices for DDGS and ethanol given prices for corn and gasoline, respectively. In models  $\Delta D$  and  $\Delta E$ , “base” price levels for the commodities are needed, with the change from the base level of the independent variable used to calculate a change from the base level of the dependent variable. This predicted change estimated by the model would then be added to the base level of the dependent variable to calculate the predicted price.

While the main objective of the differencing transformation is to correct for serial correlation, there is another advantage to this transformation. First differencing can also transform a highly persistent time-series data set into a weakly dependent data set. Weak dependence is also a requirement for OLS estimates of coefficient standard errors, and thus t-

statistics used for inference, to be valid. Highly persistent data sets can often be described as following a unit-root, or random walk process where the current period's value is determined by the previous period's value plus some mean-zero, independent random disturbance. Greene (2003) outlines the Dickey-Fuller test for a unit-root process where the time-series values are regressed on their one-period lagged values and then testing the null hypothesis that the slope coefficient estimate is significantly less than 1. The Dickey-Fuller test (at 5 percent significance) was performed on all four of the price series used in this analysis. The corn and DDGS price series rejected the null hypothesis (evidence of high persistence), while the ethanol and gasoline price series results accepted the null hypothesis (5 percent significance). In either case, differencing corrects for high persistence, if it exists, and creates a weakly dependent data set that can be estimated with OLS providing valid estimates for the standard errors, and thus t-statistics, for the coefficient estimates. A more detailed discussion of time-series analysis and serial correlation, highly persistent data, unit-root processes, and testing procedures can be found in Greene (2003) or Woolridge (2003).

### **Monte Carlo Price Simulations**

To determine fair premium levels, Monte Carlo analysis was utilized by randomly generating thirty draws of 5000 commodity prices. Each draw represented a distribution of commodity prices for a contract month. There are 12 price draws each for natural gas and unleaded gasoline prices, since these commodities have traded futures contracts for each month in the year. There are six corn price draws as traded corn futures contracts are traded for only 5 months of the year<sup>4</sup>. The sixth price draw is generated for the one year out March

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<sup>4</sup> Corn futures contracts are currently traded for March, May, July, September, and December.

contract, as it is need for interpolation purposes. All prices were assumed to follow a lognormal distribution.

The means for each price distribution were taken as the predicted prices for the 2002 contract year using the relevant futures market contract quotes, assuming futures market efficiency. Implied volatilities, adjusted for time to maturity, were taken from at-the-money options quotes from the relevant commodity markets during the first week in March of 2002, using the Black's option pricing model for futures. The annualized implied volatilities used in this research are calculated using at-the-money call option premiums and strike prices and then adjusted for time to maturity according to the following formula<sup>5</sup>:

$$\sigma = \sigma^A \sqrt{\Delta t}$$

where  $\sigma$  equals the time adjusted volatility,  $\sigma^A$  equals the annualized volatility calculated from at-the-money call option contract prices, and  $\Delta t$  equals the time to maturity, in years, for the option contract. This method for adjusting annualized volatility measures is outlined in Kolb (2003). The implied volatilities are calculated as the standard deviation of the price in percentage terms. Therefore, the time adjusted implied volatility for a given price is the standard deviation of the natural log of the given price,  $\ln(P)$ . Table A-1, included in the appendix, contains a summary of the price distribution assumptions.

In implementing the Monte Carlo procedure, incorporating the correlation among the variables is extremely important because it eliminates unrealistic price scenarios from the analysis. The desired correlation structure was calculated from historical futures prices while

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<sup>5</sup> The software program Derivagem was used to calculate the annualized implied volatilities, based on the Black option pricing model for futures.

the method proposed by Iman and Conover (1982) was used to impose the historical correlation structure.

Each set of independent price draws could have been generated in Microsoft Excel by drawing from a normal distribution with a specified mean and variance and then transforming the draws to obtain an approximation to the desired lognormal distribution of prices. Let  $\bar{P}$  be the desired mean given by the futures contract quote and  $\sigma$  be the volatility implied from the at-the-money option contract for the price distribution of interest. Let  $X$  be a normally distributed random variable with mean,  $\mu$ , and standard deviation,  $\sigma$ .

Define  $\lambda^2 = \bar{P}^2 (e^{\sigma^2} - 1)$ , and let  $\mu = \ln(\bar{P}^2) - \frac{1}{2} \ln(\bar{P}^2 + \lambda^2)$ . Then by the properties of normal and lognormal random variables the exponential of  $X$ ,  $e^X$ , is lognormally distributed with mean  $\bar{P}$ , and volatility  $\sigma$  (standard deviation in percentage terms). Unfortunately, Excel exhibits a systematic bias when this method is used. The level of the bias is directly proportional to both the mean and volatility for the distribution. For this analysis another method was used to generate the lognormally distributed prices to avoid any misspecification caused by systematic bias. First, 30 draws of 5000 random variables were generated from a standard normal distribution using Excel's random number generator. Then, the normal cumulative distribution function (cdf) value was calculated for each draw. Then each cdf value was transformed using the inverse lognormal cdf to a lognormal random variable with the specified mean,  $\bar{P}$ , and volatility,  $\sigma$ .

### **Imposing Correlation Structure**

Each price distribution was generated independently from its assumed marginal distribution. Therefore, the desired correlation structure was not yet imposed. Historical



corn futures prices from 1980 through 2002, and gasoline and natural gas price data from 1985 and 1990, respectively, through 2002 were used to calculate the historical rank correlations for the relevant prices. The difference between the predicted and actual price levels for each commodity was calculated for each contract year, taking predicted and actual prices as defined in the contract details section. Rank correlations of these price deviates were then calculated pair-wise to maximize the amount of data available. The calculated historical rank-correlation matrix is included as Figure A-1 in the appendix section.

For the Iman and Conover method to be employed, the target matrix must be positive-definite, a restriction that the calculated matrix did not meet. The historical rank correlation matrix was modified to create a positive-definite matrix that followed the same historical correlation structure. The modifications performed differ between commodities. The inter-temporal correlations for the corn price deviates were left unchanged. The inter-commodity and inter-temporal correlations between the corn, unleaded gasoline, and natural gas price deviates were set at their respective average values. The inter-temporal correlations for the unleaded gasoline and natural gas price deviates were transformed using the following linear regression model:

$$RankCorr_{i,j} = \alpha + \beta * Lag_{i,j} + \varepsilon_{i,j} \quad (3)$$

where:  $RankCorr_{i,j}$  = Inter-temporal rank correlation between months  $i$  and  $j$   
 $Lag_{i,j}$  = time lag, in months, between months  $i$  and  $j$   
 $\varepsilon_{i,j}$  = zero-mean, homoskedastic error term for lag between months  $i$  and  $j$

For example, the January and March natural gas contracts have a time lag of 2 months. The dependent variable in the estimated model would be the value of the calculated

correlation between January and March natural gas price deviations, while the independent variable for that data point would equal the time lag of 2 months.

The score matrix (R) was constructed from 30 columns of 5000 van der Waerden scores. The van der Waerden scores were randomly mixed within each column. The Iman and Conover method was applied to the random draws of 5000 prices using a C++ computer program written by Chad Hart, Iowa State University. However, if the analysis had used fewer draws, the technique could have been conducted within a standard spreadsheet program such as Excel. Given the target historical rank correlation matrix (T) and the random score matrix (R), the Iman and Conover technique solves for the transformation matrix (S) where the product (RS') has a correlation matrix equal to T and a rank correlation matrix close to T. The transformed matrix of Monte Carlo simulations (RS') was then ranked by column from 1 to 5000 after the Iman and Conover technique was applied.

The actual rank correlation matrix of the transformed Monte Carlo data is included in the appendix as Figure A-3. Also included in the appendix, as Figure A-4, is a matrix of the differences between the target matrix and the correlation matrix of the random draws. The largest difference between the target and actual rank correlation values (in absolute value) is 0.026. Therefore the Iman and Conover method provides a good approximation of the target historical relationships.

### **Premium Determination**

Each Monte Carlo simulation can be interpreted as a possible price scenario for the contract year. The actual gross margin for an ethanol plant is calculated given the price scenario for each of the 5000 simulations according to equation 1. The difference between the simulated actual gross margins and the margin guarantee for the contract year (2002) is

then calculated. The option value to the owner is then equal to this difference, if positive, and zero otherwise. The option value is calculated for each of the 5000 simulations and then averaged to determine the fair premium rate for the insurance product. The per bushel premium rates are calculated in dollar terms, and then translated into percentage terms of the margin guarantee for use in other contract years.

### **Contract Settlement**

At contract termination, contract owners receive an indemnity payment for each bushel insured based on the following formula:

$$\text{Indemnity} = \max[0, \text{MarGuar} - \text{MarAct}]$$

where:

*MarGuar* = the gross margin guarantee for the contract year

*MarAct* = the actual gross margin for the contract year

The margin guarantee is calculated using predicted commodity price levels using equation 1, whereas the actual gross margin level is calculated using the actual price levels and equation 1. In determining the fair premium rates, actual price levels were taken as the simulated values. In practice, to settle the contract, actual price levels are taken as the average settlement price over the last 10 trading days of the settlement month for corn, and the average over the entire settlement month for unleaded gasoline and natural gas. Again, the pricing models outlined previously (models D, E,  $\Delta D$ , and  $\Delta E$ ) are used to calculate actual and predicted price levels for ethanol and DDGS using the futures prices for gasoline and corn respectively. Producers will be required to provide receipts of actual corn marketings to their facility at contract termination so that premiums and indemnity payments can be adjusted if actual marketings differ from expected marketings at the time of contract purchase. Since the value of this product is determined solely by futures contract prices, the

moral hazard problem is minimized. Individual producers do not have the ability to affect futures price levels, and therefore cannot affect the likelihood of receiving payments. Additionally, basing the product formulation on the assumption of a fixed proportions technology eliminated the problem of adverse selection. Riskier producers have no more incentive to purchase the product than less risky producers, where producer “riskiness” is defined in terms of efficiency of the respective ethanol cooperative in which they hold membership.

## RESULTS

### Pricing Model Estimates

Both the slope and intercept estimates for model D were found to be significant at a one percent significance level. Both the constant and slope coefficient estimates for Model E were also found to be statistically significant at a one percent significance level. The coefficient estimates, standard errors, t-statistics, p-values, and  $R^2$  values for both pricing models are reported in Table 1. While the  $R^2$  values seem to be rather low, the accuracy of the models is compared to the accuracy displayed in futures markets in the following subsection.

**Table 1: Summary Statistics for Models D and E**

Model	Dependent Variable	Independent Variable	$\hat{\alpha}$ (S.E.)	t-stat (p-value)	$\hat{\beta}$ (S.E.)	t-stat (p-value)	$R^2$
D	$DDGP_t$ (\$/ton)	$CORNP_t$ (\$/bu)	19.52 (7.04)	2.77 (0.007)	33.996 (2.700)	12.61 (0.00)	0.6
E	$ETHP_t$ (\$/gal)	$UNLP_t$ (\$/gal)	0.72 (0.04)	17.15 (0.000)	0.82 (0.067)	12.37 (0.00)	0.42

The coefficient estimates show that for every ten cent per bushel increase in the price of corn, the price for DDGS can be expected to increase by about 34 dollars per ton on average. For every ten cent per gallon increase in the price of unleaded gasoline, the price of ethanol is expected to increase by about eight cents per gallon on average.

### Root Mean Square Error Analysis

Table 2 reports the RMSE for each commodity in each commodity's typical measure of price per unit as well as on a percentage basis for comparison across markets. The base price levels used in calculating the percentage RMSE were taken as the average over the predicted and actual price levels for each commodity. The RMSE measures for corn,

unleaded gasoline, and natural gas reflect the accuracy of the futures markets over the historical period analyzed. Table 2 shows that the levels of accuracy achieved by the pricing models are quite comparable to the level of accuracy exhibited in the futures markets. In fact, the 14 percent and 16.6 percent levels of error calculated for the ethanol and DDGS regression models, respectively, are considerably lower than the levels of error in the futures markets for unleaded gasoline and natural gas.

**Table 2: RMSE Comparisons Across Commodities**

	Market	RMSE	Average Price Level	RMSE (%)
Corn (\$/bu)	Futures	\$0.40	\$2.60	15.4%
Unleaded Gasoline (\$/gal)	Futures	\$0.12	\$0.60	19.6%
Natural Gas (\$/gal)	Futures	\$1.17	\$2.53	46.4%
Ethanol (\$/gal)	Regression	\$0.17	\$1.21	14.0%
DDGS (\$/ton)	Regression	\$17.45	\$105.14	16.6%

### Serial Correlation

The coefficient estimates, standard errors, t-statistics, and p-values for the tests for serial correlation are reported for each pricing model (D and E) in Table 3. The results show strong evidence of 1<sup>st</sup> order serial correlation (both rejected  $H_0: \rho = 0$  at 1 percent), therefore the data was transformed to correct for this problem by differencing each price series and estimating differenced regression models.

**Table 3: Testing for Serial Correlation in Models D and E**

Model	Dependent Variable	Independent Variable	$\rho$ (S.E.)	t-stat (p-value)
D	$\hat{\varepsilon}_t$ (\$/ton)	$\hat{\varepsilon}_{t-1}$ (\$/ton)	0.87 (0.035)	24.72 (0)
E	$\hat{\varepsilon}_t$ (\$/gal)	$\hat{\varepsilon}_{t-1}$ (\$/gal)	0.85 (0.052)	16.10 (0)

### Differenced Pricing Model Estimates

The coefficient estimates, standard errors, t-statistics and p-values for models  $\Delta D$  and  $\Delta E$  are summarized in Table 4. The coefficient estimates were all significant at a five percent significance level. The estimates imply that a ten cent per bushel change in the price of corn will lead to a \$1.80 per ton change in the price of DDGS on average. A ten cent per gallon change in the price of unleaded gasoline is consistent with a 4.5 cent per gallon change in the price of ethanol on average.

**Table 4: Summary Statistics for Models  $\Delta D$  and  $\Delta E$** 

Model	Dependent Variable	Independent Variable	$\hat{\beta}$ (S.E.)	t-stat (p-value)
$\Delta D$	$\Delta DDGP_t$ (\$/ton)	$\Delta CORNP_t$ (\$/bu)	11.79 (4.97)	2.37 (0.02)
$\Delta E$	$\Delta ETHP_t$ (\$/gal)	$\Delta UNLP_t$ (\$/gal)	0.45 (0.07)	6.48 (0)

### Rank Correlation Model Estimates

The coefficient estimates, standard errors, and t-statistics for the rank correlation models are summarized in Table 5. The coefficient estimates were found to be statistically significant at 1 percent for both models. The estimated slope coefficients were negative for both models, which implies that as the time lag between contracts gets larger the correlation

decreases, which parallels the correlation structure in the historical matrix. The modified target rank correlation matrix is included in the appendix as Figure A-2.

**Table 5: Summary Statistics for the Rank Correlation Regression Models**

Model	Dependent Variable	Independent Variable	$\hat{\alpha}$ (S.E.)	t-stat (p-value)	$\hat{\beta}$ (S.E.)	t-stat (p-value)
3	Unleaded Correlations	Time lag (months)	0.71 (0.055)	12.84 (0)	-0.052 (0.011)	-4.75 (0)
3	Natural Gas Correlations	Time lag (months)	0.82 (0.034)	23.96 (0)	-0.024 (0.007)	-3.61 (0)

### Premium Rates

Using the formulation for calculating the margin guarantee and actual gross margin level using equation 1, fair premiums were determined for the 2002 contract year from predicted prices and using the transformed Monte Carlo draws as 5000 simulated actual price scenarios. Premiums and indemnities were calculated at various coverage levels using both types of DDGS and ethanol price prediction models outlined previously. Table 6 summarizes the margin guarantees and fair premiums at various coverage levels. The margin guarantee and premiums calculated using models D and E for predicting prices are denoted by LEVEL. The margin guarantee and premiums calculated using models  $\Delta D$  and  $\Delta E$  are denoted by DIFF. Table 7 reports the base price levels used with the DIFF pricing models. The base price levels for corn and unleaded gasoline were taken as actual March futures prices in the contract year. The base levels for DDGS and ethanol were taken as the average of the actual spot prices for March from the data sets described previously.

Premium levels are very similar for both pricing models used. However, the premiums calculated using the DIFF pricing models are a higher percentage of the margin



guarantee. At full coverage, the LEVEL pricing models yielded an 8.6 percent premium, while the DIFF models yielded an 11.7 percent premium. As the level of coverage is lowered to 85 percent, the premiums fall to 3.1 percent and 6.1 percent of the margin guarantee for the LEVEL and DIFF models, respectively. For the 2002 contract year, as the level of coverage falls, the DIFF premiums become relatively higher than the premium rates calculated using the LEVEL pricing models. The distribution of the uninsured actual gross margin values is illustrated in Figures 3 for the LEVEL models and in Figure 4 for the DIFF pricing models. The figures show the dispersion of actual gross margin scenarios under the distributional assumptions of the Monte Carlo simulations.

**Table 6: Per Bushel Premiums (\$/bu) at Various Coverage Levels**

Pricing Model	Margin Guarantee	Premiums by Coverage Level (% of Margin Guarantee)			
		100%	95%	90%	85%
LEVEL	\$1.57	\$0.135 (8.6%)	\$0.099 (6.3%)	\$0.071 (4.5%)	\$0.049 (3.1%)
DIFF	\$1.13	\$0.132 (11.7%)	\$0.107 (9.5%)	\$0.086 (7.6%)	\$0.068 (6.1%)

**Table 7: Base Price Levels Used for DIFF Models**

Commodity	Base Price
Ethanol	\$1.12/gal
Unleaded Gasoline	\$0.59/gal
DDGS	\$79.00/ton
Corn	\$2.02/bu.

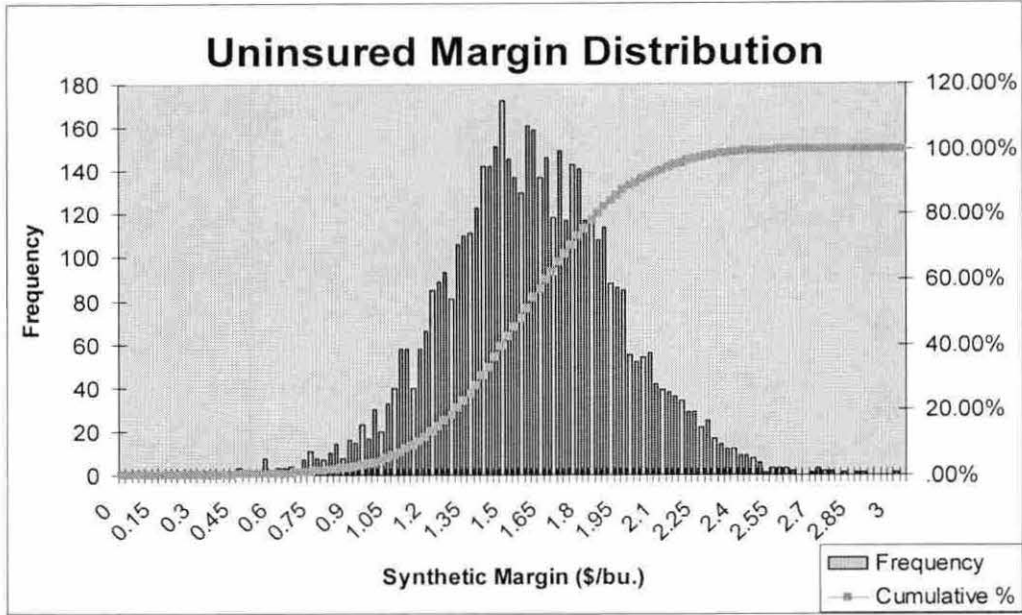
While the mean levels of gross margin differ according to the pricing models used, the dispersion of possible gross margin scenarios about the mean is similar regardless of which pricing models are used in the Monte Carlo analysis. Figures 5 and 6 illustrate the

distribution of gross margins scenarios when insurance is purchased at a coverage level of 85 percent for the LEVEL and DIFF pricing models, respectively. Roughly 35 percent of the downside risk is eliminated through the purchase of the insurance. However, there is a risk-reward tradeoff in that the possibilities of earning high levels of gross margin are somewhat lowered. Figures A-5 through A-10, included in the appendix, illustrate the distribution of gross margin scenarios at the other coverage levels for both the LEVEL and DIFF pricing models.

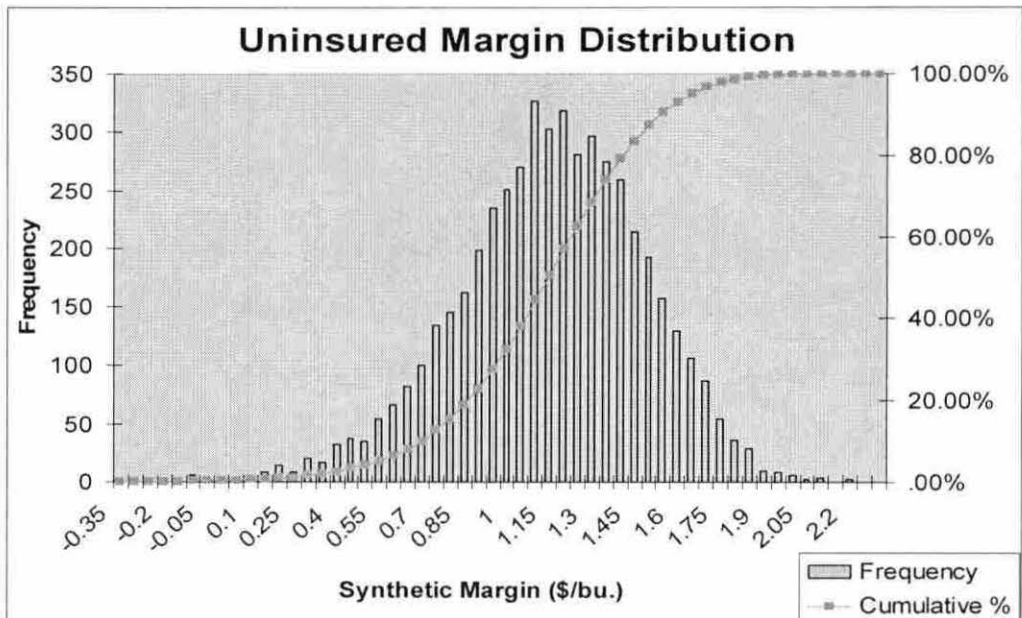
While the structure of the product is the same for both sets of pricing models, the marginal effects of price changes for each commodity on the value of the product is different for each pricing model used. Table 8 summarizes the marginal effects of price movements for each commodity. The marginal effects are reported as the change in value, per bushel, of the insurance claim for a ten cent increase in the average actual price level from the average predicted price level for that commodity, holding all else constant.

**Table 8: Marginal Effects on Product Value (\$/bu), by Commodity**

Pricing Model	Marginal Effect on Product Value (for \$0.10 increase in price)		
	Unleaded (\$/gal)	Corn (\$/bu)	Natural Gas (\$/gal)
LEVEL	(\$0.221)	\$0.071	\$0.017
DIFF	(\$0.122)	\$0.090	\$0.017



**Figure 3: Distribution of Uninsured Gross Margins (\$/bu)-LEVEL**



**Figure 4: Distribution of Uninsured Gross Margins (\$/bu)-DIFF**

The marginal effects of price changes in the gasoline market have a marginal effect three times as large as that of price changes in the corn market when the product is structured using the LEVEL pricing models. Under the DIFF models the marginal effects of price changes in the corn and gasoline markets are more even, with the gasoline market having a slightly larger effect on the value of the product. This may provide more support for using the DIFF models rather than the level models beyond the statistical properties analyzed earlier. Since this product is aimed at corn producers, they may find it more valuable to have relatively more weight on corn price volatility in determining the value of the insurance product. However, the LEVEL models may be viewed as the simpler alternative. The LEVEL models also have the benefit of the product being structured using only futures prices. Futures markets are very large and liquid markets relative to any corn producer. Using only futures prices eliminates the moral hazard problem of an agent having the ability to affect the value of the product. The DIFF models require some kind of spot market base level, which could create moral hazard problems. Using some type of regional average as the base price level for ethanol and DDGS can eliminate this problem. It should be noted that in using either model, there are opposing forces on the total marginal effect of changes in the corn price. Corn is used as an input to the process, which increases the product value when actual prices are higher than predicted. However, changes in corn prices have positive marginal effects on the actual price used for DDGS in determining the value of the product at termination. Therefore changes in corn prices also decrease the product value through the determination of actual DDGS price levels used in contract settlement.

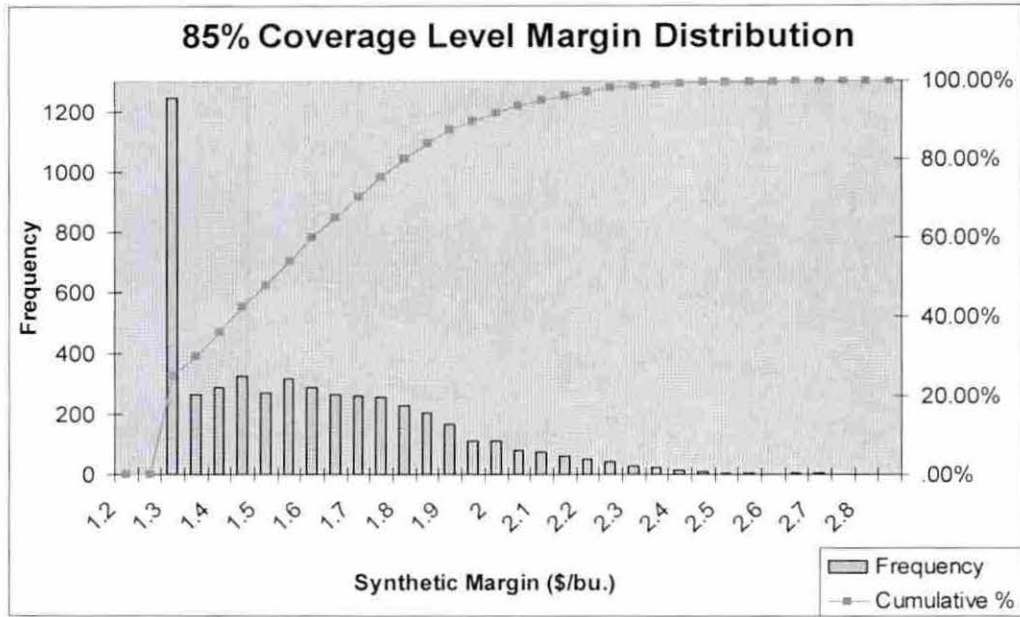


Figure 5: Distribution of Gross Margins (\$/bu) at 85% Coverage-LEVEL

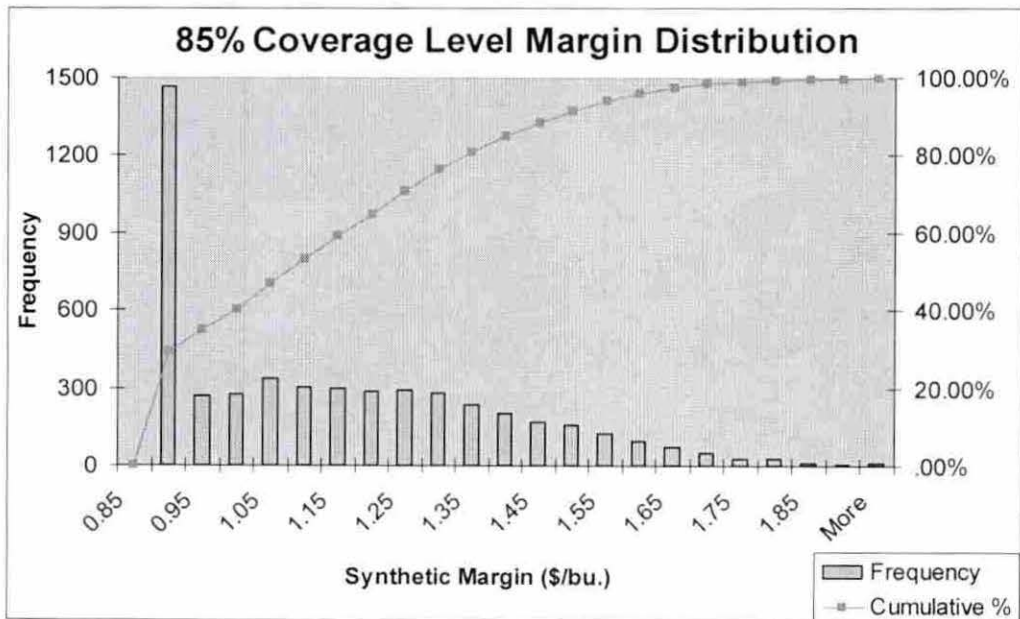


Figure 6: Distribution of Gross Margins (\$/bu) at 85% Coverage-DIFF

### Historical Analysis

Margin guarantees, actual margins, and indemnity payments were calculated using the LEVEL models from 1991 through 2003. Margin guarantees and actual margins were calculated using the DIFF models from 1994 through 2003, with base levels calculated in the same manner as they were in the previous section. Historical premiums were also calculated based on the percentages of the margin guarantee taken from the Monte Carlo results for the 2002 contract year for the various coverage levels. Tables 9 and 10 summarize these results for the LEVEL and DIFF pricing models respectively.

**Table 9: Margins, Indemnities, and Premiums – LEVEL Models**

Policy Year	Margin		Indemnities					Premiums		
	Guarantee	Actual	100%	95%	90%	85%	100%	95%	90%	85%
1991	\$1.25	\$1.52	\$0.00	\$0.00	\$0.00	\$0.00	\$0.11	\$0.08	\$0.06	\$0.04
1992	\$1.17	\$1.51	\$0.00	\$0.00	\$0.00	\$0.00	\$0.10	\$0.07	\$0.05	\$0.04
1993	\$1.44	\$1.06	\$0.38	\$0.30	\$0.23	\$0.16	\$0.12	\$0.09	\$0.06	\$0.04
1994	\$0.79	\$1.31	\$0.00	\$0.00	\$0.00	\$0.00	\$0.07	\$0.05	\$0.04	\$0.02
1995	\$1.24	\$0.79	\$0.45	\$0.39	\$0.33	\$0.26	\$0.11	\$0.08	\$0.06	\$0.04
1996	\$0.53	\$0.48	\$0.05	\$0.03	\$0.00	\$0.00	\$0.05	\$0.03	\$0.02	\$0.02
1997	\$0.99	\$1.12	\$0.00	\$0.00	\$0.00	\$0.00	\$0.09	\$0.06	\$0.04	\$0.03
1998	\$0.85	\$1.16	\$0.00	\$0.00	\$0.00	\$0.00	\$0.07	\$0.05	\$0.04	\$0.03
1999	\$1.08	\$1.66	\$0.00	\$0.00	\$0.00	\$0.00	\$0.09	\$0.07	\$0.05	\$0.03
2000	\$1.67	\$1.83	\$0.00	\$0.00	\$0.00	\$0.00	\$0.14	\$0.11	\$0.07	\$0.05
2001	\$1.28	\$1.76	\$0.00	\$0.00	\$0.00	\$0.00	\$0.11	\$0.08	\$0.06	\$0.04
2002	\$1.57	\$1.61	\$0.00	\$0.00	\$0.00	\$0.00	\$0.14	\$0.10	\$0.07	\$0.05
2003	\$1.50	\$1.47	\$0.03	\$0.00	\$0.00	\$0.00	\$0.13	\$0.09	\$0.07	\$0.05
<b>Total</b>			<b>\$0.91</b>	<b>\$0.72</b>	<b>\$0.56</b>	<b>\$0.42</b>	<b>\$1.32</b>	<b>\$0.97</b>	<b>\$0.69</b>	<b>\$0.48</b>

With premiums calculated as a percentage of the margin guarantee for the contract year, premium levels and margin guarantees are directly proportional to each other. Structuring the product with the LEVEL pricing models, indemnities payments were paid in 1993, 1994, and 1996. Using the DIFF pricing models in structuring the product yielded similar results in that indemnities were also paid in 1994 and 1996. However, the actual value of the indemnities differed, due to the differences in how the pricing models project the

levels of guaranteed and actual gross margins. 1993, 1994, and 1996 were years of high volatility in the corn futures markets. The predicted prices for corn were well below the actual levels in all three years. The predictions were \$0.18, \$0.56, and \$0.34 below the actual values for 1993, 1994, and 1996 respectively. The price of unleaded gasoline was over-predicted in 1993 (\$0.08), which also increased the value of the product. In 1994 and 1996 unleaded gasoline prices were under-predicted by \$0.02 and \$0.12 respectively, but these effects were outweighed by the extreme volatility in the corn market for those years. These results confirm achievement of the objective in developing this product. The policy has value under conditions of extreme price volatility.

The value of the stream of indemnity payments is less than the stream of premium payments<sup>6</sup> required to carry the product over the historical period analyzed. However, as the level of coverage decreases, the difference between the two streams of payments decreases. This implies that producers would have been better off buying lower levels of coverage over the period analyzed, regardless of which pricing models were used to structure the product. The fact that the premium stream is larger than the indemnity

**Table 10: Margins, Indemnities, and Premiums – DIFF Models**

Policy Year	Margin		Indemnities				Premiums			
	Guarantee	Actual	100%	95%	90%	85%	100%	95%	90%	85%
1994	\$1.01	\$1.55	\$0.00	\$0.00	\$0.00	\$0.00	\$0.12	\$0.10	\$0.08	\$0.06
1995	\$1.18	\$0.58	\$0.60	\$0.54	\$0.48	\$0.42	\$0.14	\$0.11	\$0.09	\$0.07
1996	\$0.72	\$0.49	\$0.23	\$0.20	\$0.16	\$0.12	\$0.08	\$0.07	\$0.05	\$0.04
1997	\$0.96	\$1.13	\$0.00	\$0.00	\$0.00	\$0.00	\$0.11	\$0.09	\$0.07	\$0.06
1998	\$0.54	\$1.05	\$0.00	\$0.00	\$0.00	\$0.00	\$0.06	\$0.05	\$0.04	\$0.03
1999	\$0.98	\$1.40	\$0.00	\$0.00	\$0.00	\$0.00	\$0.12	\$0.09	\$0.07	\$0.06
2000	\$0.79	\$0.90	\$0.00	\$0.00	\$0.00	\$0.00	\$0.09	\$0.07	\$0.06	\$0.05
2001	\$1.59	\$2.19	\$0.00	\$0.00	\$0.00	\$0.00	\$0.19	\$0.15	\$0.12	\$0.10
2002	\$1.13	\$1.01	\$0.11	\$0.06	\$0.00	\$0.00	\$0.13	\$0.11	\$0.09	\$0.07
2003	\$0.93	\$0.95	\$0.00	\$0.00	\$0.00	\$0.00	\$0.11	\$0.09	\$0.07	\$0.06
<b>Total</b>			<b>\$0.95</b>	<b>\$0.79</b>	<b>\$0.64</b>	<b>\$0.55</b>	<b>\$1.15</b>	<b>\$0.93</b>	<b>\$0.75</b>	<b>\$0.60</b>

<sup>6</sup> The indemnities and premiums are reported in nominal terms with no time discounting.

stream is an interesting result. A fair premium, by definition, should equate the payments received from the product to the cost of carrying the product over a period of time. It may be possible that the time period analyzed was simply too small, but ethanol production did not become a major enterprise for corn producers until the early 1990's. Therefore, analyzing older historical price data may not reflect true relationships. Another possible reason for these results is the presence of bias in the futures markets for the commodities used in structuring the product. The accuracy of the predictions for each commodity price market was analyzed for each period. On average the predicted price of unleaded gasoline was \$0.05 (7.38%) lower than the actual price levels used in contract settlement. The predicted prices for natural gas also exhibited a negative bias of \$0.19 (7.68%). The predicted prices for corn were, on average, \$0.12 (4.69%) higher than the actual prices used in contract settlement. The negative and positive bias in the gasoline and corn markets, respectively, both cause a decrease in the value of the product. The negative bias in the natural gas market would increase the value of the product, but the marginal effect of changes in natural gas prices was shown to be marginally small relative to the effects of changes in corn and gasoline prices. It should be noted that these biases are calculated only as averages over the historical period analyzed. Futures market bias should be virtually eliminated by arbitrage, on average, if examined over a longer time interval.

### **Sensitivity Analysis**

To determine the effect of price volatility on the premium rates for the product, fair premiums were calculated using higher levels of volatility in the Monte Carlo price draws. Volatilities were increased for each commodity price draw by ten percent. Table A-2, included in the Appendix, reports the higher volatilities imposed on the price distributions



used for premium determination. The premiums are reported in Table 11 for both the LEVEL and DIFF pricing models. Increasing the price volatilities by ten percent causes the premium levels to increase. Higher volatility implies more uncertainty, which raises the fair cost of the product. The higher volatility cause the premium rates to increase from 8.6 percent and 11.7 percent to 11.5 percent and 16.3 percent of the margin guarantee at 100 percent coverage for the LEVEL and DIFF models respectively. Again, at full coverage the premiums are roughly equivalent, but as the level of coverage falls the calculated premiums using the DIFF pricing models become relatively more expensive the LEVEL model premiums.

**Table 11: Per Bushel Premiums at Various Coverage Levels, 10% Higher Volatility**

Pricing Model	Margin Guarantee	Premiums by Coverage Level (% of Margin Guarantee)			
		100%	95%	90%	85%
LEVEL	\$1.57	\$0.181 (11.5%)	\$0.145 (9.2%)	\$0.114 (7.2%)	\$0.089 (5.6%)
DIFF	\$1.13	\$0.184 (16.3%)	\$0.159 (14.1%)	\$0.137 (12.2%)	\$0.118 (10.4%)

At the higher levels of price volatility, the actual premium rates increase by about 39 percent at full coverage for both pricing models. At 95 percent coverage, the premium rates increase by about 48 percent for both pricing models. At 90 percent coverage, the premium rates increase by about 60 percent for both pricing models. As the coverage level falls to 85 percent, the premiums rates increase by over 70 percent for both pricing models. This implies that premiums at all levels of coverage are extremely sensitive to the level of volatility assumed for the commodity prices. Premiums at lower levels of coverage are relatively more sensitive to the level of assumed price volatility.

## CONCLUSIONS

### General Conclusions

Currently there are a wide variety of insurance products available to agricultural producers to insure against yield or price risks in the markets for the raw commodities in which they produce. Over the last decade farmers have been diversifying by becoming involved with value-added enterprises such as ethanol production. This research developed an insurance product aimed at corn producers who are members in an ethanol production cooperative. The product has the potential to provide these producers a new and useful risk management tool.

The product is structured to insure against price risks in the markets for corn, DDGS, ethanol, and natural gas. Futures prices for corn, unleaded gasoline, and natural gas were used to develop two different pricing models, which were used to structure the product to insure the gross margin level of an ethanol production facility on a per bushel basis. The gross margin was chosen as it should provide an adequate proxy for premium payments the producer would receive from the facility. Both pricing models are statistically unbiased estimators of the DDGS and ethanol prices, but provide two different structures for the product. Both pricing models were also shown to exhibit a comparable level of accuracy to the futures markets for corn, unleaded gasoline, and natural gas.

Monte Carlo analysis was used to develop fair premiums at various coverage levels. A historical correlation structure was imposed on the simulated price data using a method proposed by Iman and Conover, which maintains the marginal distributions of the variables. Premiums were calculated based on both pricing models at various coverage levels. The relative size of the marginal effects of price movements for each commodity differs between

the two models. Therefore, the two pricing models yielded slightly different premium structures.

Historical analysis was carried out to examine how the product would have performed had it been offered over the last decade, comparing the results for both pricing models. The product was shown to perform as was intended, paying indemnities in years of extreme price volatility. The stream of indemnity payments was shown to be smaller than the stream of premium payments required to carry the product over the historical period analyzed. This result may come from the fact that the historical period analyzed was relatively small, or from bias exhibited in the futures markets for corn and unleaded gasoline over the historical period analyzed.

Sensitivity analysis was also performed to determine the effect of volatility levels on the fair premiums. As expected, premium rates increased as the level of price volatility was increased. This effect was shown to be more severe as the level of coverage decreased.

### **Future Research**

This product was rated using pricing proxies for ethanol and DDGS prices because there were no future markets for either of these commodities when this research was conducted. With the introduction of ethanol futures markets both on the NYBOT and CBOT forthcoming, there is the potential to reconduct this analysis and to more accurately price the product. Eliminating the use of a regression pricing model will remove more of the error and variability in calculating the fair premium rates. Gasoline prices were shown to have a fairly strong correlation to cash ethanol prices in the Midwest, but a true ethanol futures contract would theoretically be a much more accurate index of cash ethanol prices in all regions of the U.S.

Other applicable areas include other value-added industries. The biodiesel industry has also seen extensive growth over the last 5 years, as soybean farmers have started to turn to this young industry to diversify and find new markets for what they produce. Biodiesel plants are in the planning and construction phases all across the U.S., many of which are being built as farmer owned cooperatives similar to the already existing ethanol cooperatives. As farmers continue to find new markets and new techniques to market their products, there will need to be new advances in the area of risk management to create new risk management tools for these farmers to hedge against the risks embodied in their new ventures.

## APPENDIX

Table A-1: Price Distribution Assumptions, Actual Implied Volatilities

Price Variable	Distribution Assumptions		
	Mean	Annualized Volatility	Adjust Volatility*
Mar Corn	\$2.01	-	-
May Corn	\$2.08	17.1%	7.0%
July Corn	\$2.15	20.0%	11.5%
Sep Corn	\$2.22	25.2%	17.8%
Dec Corn	\$2.30	22.3%	19.3%
Mar+1 Corn	\$2.39	19.7%	19.7%
Jan+1 Unl	\$0.64	36.7%	33.5%
Feb+1 Unl	\$0.65	36.7%	35.1%
Mar+1 Unl	\$0.65	36.7%	36.7%
Apr Unl	\$0.73	39.6%	11.4%
May Unl	\$0.74	41.7%	17.0%
June Unl	\$0.74	42.3%	21.1%
July Unl	\$0.73	40.4%	23.3%
Aug Unl	\$0.71	39.4%	25.4%
Sep Unl	\$0.69	38.1%	26.9%
Oct Unl	\$0.66	36.7%	28.0%
Nov Unl	\$0.65	36.7%	29.9%
Dec Unl	\$0.64	36.7%	31.7%
Jan+1 NG	\$3.41	45.1%	41.2%
Feb+1 NG	\$3.35	48.3%	46.3%
Mar+1 NG	\$3.25	41.7%	41.7%
Apr NG	\$2.53	48.6%	14.0%
May NG	\$2.57	46.8%	19.1%
June NG	\$2.63	43.5%	21.7%
July NG	\$2.68	43.1%	24.9%
Aug NG	\$2.73	43.5%	28.1%
Sep NG	\$2.74	43.7%	30.9%
Oct NG	\$2.78	43.8%	33.5%
Nov NG	\$3.04	44.3%	36.2%
Dec NG	\$3.30	44.8%	38.8%

\*Based on time to maturity.

Note: +1 refers to the following calendar year.

**Table A-2: Price Distribution Assumptions, Increased Volatility**

Price Variable	Distribution Assumptions		
	Mean	Annualized Volatility	Adjusted Volatility*
Mar Corn	\$2.01	-	-
May Corn	\$2.08	27.1%	11.1%
July Corn	\$2.15	30.0%	17.3%
Sep Corn	\$2.22	35.2%	24.9%
Dec Corn	\$2.30	32.3%	27.9%
Mar+1 Corn	\$2.39	29.7%	29.7%
Jan+1 Unl	\$0.64	46.7%	42.6%
Feb+1 Unl	\$0.65	46.7%	44.7%
Mar+1 Unl	\$0.65	46.7%	46.7%
Apr Unl	\$0.73	49.6%	14.3%
May Unl	\$0.74	51.7%	21.1%
June Unl	\$0.74	52.3%	26.1%
July Unl	\$0.73	50.4%	29.1%
Aug Unl	\$0.71	49.4%	31.9%
Sep Unl	\$0.69	48.1%	34.0%
Oct Unl	\$0.66	46.7%	35.6%
Nov Unl	\$0.65	46.7%	38.1%
Dec Unl	\$0.64	46.7%	40.4%
Jan+1 NG	\$3.41	55.1%	50.3%
Feb+1 NG	\$3.35	58.3%	55.8%
Mar+1 NG	\$3.25	51.7%	51.7%
Apr NG	\$2.53	58.6%	16.9%
May NG	\$2.57	56.8%	23.2%
June NG	\$2.63	53.5%	26.7%
July NG	\$2.68	53.1%	30.7%
Aug NG	\$2.73	53.5%	34.5%
Sep NG	\$2.74	53.7%	38.0%
Oct NG	\$2.78	53.8%	41.1%
Nov NG	\$3.04	54.3%	44.3%
Dec NG	\$3.30	54.8%	47.4%

\*Based on time to maturity.

Note: +1 refers to the following calendar year.

	Mar Com	May Com	July Com	Sep Com	Dec Com	Mar+1 Co	Jan+1 Uhl	Feb+1 Uhl	Mar+1 Uhl	Apr Uhl	May Uhl	June Uhl	July Uhl	Aug Uhl	Sep Uhl	Oct Uhl	Nov Uhl	Dec Uhl
Mar Com	1.000	0.310	-0.117	-0.110	-0.176	-0.164	0.226	0.346	0.257	0.245	0.042	0.137	0.051	0.205	0.139	0.276	0.170	0.135
May Com	0.310	1.000	0.580	0.328	0.322	0.334	0.358	0.536	0.364	0.195	-0.026	0.139	0.133	0.139	0.238	0.412	0.321	0.348
July Com	-0.117	0.580	1.000	0.774	0.597	0.686	0.174	0.255	0.129	0.245	0.313	0.141	-0.119	-0.082	-0.141	0.065	-0.022	-0.038
Sep Com	-0.110	0.328	0.774	1.000	0.820	0.888	0.245	0.286	0.255	0.259	0.154	-0.024	-0.154	0.112	0.065	0.079	0.053	0.030
Dec Com	-0.176	0.322	0.597	0.820	1.000	0.848	-0.150	-0.009	-0.024	0.077	-0.065	-0.088	-0.125	-0.123	-0.247	-0.156	-0.201	-0.224
Mar+1 Com	-0.164	0.334	0.686	0.888	0.848	1.000	0.224	0.288	0.284	0.112	-0.057	-0.135	-0.090	0.129	0.059	0.011	0.046	0.077
Jan+1 Uhl	0.226	0.358	0.174	0.245	-0.150	0.224	1.000	0.785	0.725	0.393	0.218	0.298	0.465	0.678	0.761	0.779	0.798	0.825
Feb+1 Uhl	0.346	0.536	0.255	0.286	-0.009	0.288	0.785	1.000	0.957	0.490	0.168	0.222	0.490	0.657	0.593	0.606	0.633	0.643
Mar+1 Uhl	0.257	0.364	0.129	0.255	-0.024	0.284	0.725	0.957	1.000	0.391	0.137	0.243	0.523	0.686	0.567	0.490	0.548	0.581
Apr Uhl	0.245	0.195	0.245	0.259	0.077	0.112	0.393	0.490	0.391	1.000	0.719	0.457	0.300	0.424	0.214	0.364	0.337	0.313
May Uhl	0.042	-0.026	0.313	0.154	-0.065	-0.057	0.218	0.168	0.137	0.719	1.000	0.773	0.319	0.152	-0.127	0.096	0.018	0.007
June Uhl	0.137	0.139	0.141	-0.024	-0.088	-0.135	0.298	0.222	0.243	0.457	0.773	1.000	0.480	0.154	0.040	0.203	0.038	0.090
July Uhl	0.051	0.133	-0.119	-0.154	-0.125	-0.090	0.465	0.490	0.523	0.300	0.319	0.480	1.000	0.721	0.294	0.408	0.457	0.453
Aug Uhl	0.205	0.139	-0.082	0.112	-0.123	0.129	0.678	0.657	0.686	0.424	0.152	0.154	0.721	1.000	0.666	0.585	0.750	0.765
Sep Uhl	0.139	0.238	-0.141	0.065	-0.247	0.059	0.761	0.593	0.567	0.214	-0.127	0.040	0.294	0.666	1.000	0.837	0.891	0.893
Oct Uhl	0.276	0.412	0.065	0.079	-0.156	0.011	0.779	0.606	0.490	0.364	0.096	0.203	0.408	0.585	0.837	1.000	0.928	0.816
Nov Uhl	0.170	0.321	-0.022	0.053	-0.201	0.046	0.798	0.633	0.548	0.337	0.018	0.038	0.457	0.750	0.891	0.928	1.000	0.946
Dec Uhl	0.135	0.348	-0.038	0.030	-0.224	0.077	0.825	0.643	0.581	0.313	0.007	0.090	0.453	0.765	0.893	0.816	0.946	1.000
Jan+1 NG	0.427	0.804	0.259	0.392	0.252	0.343	0.622	0.643	0.608	0.070	-0.119	0.147	0.469	0.531	0.483	0.664	0.594	0.497
Feb+1 NG	0.399	0.790	0.315	0.371	0.280	0.364	0.517	0.566	0.510	-0.105	-0.175	0.007	0.350	0.420	0.287	0.476	0.462	0.329
Mar+1 NG	0.280	0.692	0.315	0.455	0.455	0.483	0.399	0.503	0.483	-0.105	-0.217	-0.028	0.336	0.371	0.294	0.462	0.413	0.210
Apr NG	0.308	0.469	0.650	0.650	0.238	0.483	0.287	0.350	0.231	0.224	0.140	-0.224	-0.126	0.098	-0.028	0.189	0.175	0.000
May NG	0.483	0.483	0.378	0.350	0.098	0.294	0.385	0.441	0.364	0.112	-0.035	-0.224	-0.021	0.308	0.147	0.308	0.364	0.189
June NG	0.259	0.601	0.119	0.315	0.294	0.322	0.406	0.503	0.517	0.028	-0.308	-0.175	0.259	0.483	0.420	0.545	0.524	0.336
July NG	0.406	0.692	0.105	0.217	0.042	0.168	0.657	0.706	0.685	0.105	-0.147	0.021	0.490	0.664	0.531	0.685	0.692	0.573
Aug NG	0.392	0.699	0.042	0.070	-0.098	0.049	0.524	0.559	0.531	-0.063	-0.231	-0.021	0.469	0.538	0.420	0.573	0.573	0.531
Sep NG	0.287	0.587	-0.123	0.049	0.070	0.112	0.399	0.469	0.497	-0.056	-0.399	-0.084	0.448	0.524	0.490	0.587	0.552	0.476
Oct NG	0.189	0.413	-0.224	0.070	0.189	0.105	0.259	0.315	0.364	-0.042	-0.552	-0.231	0.294	0.434	0.448	0.559	0.476	0.350
Nov NG	0.308	0.517	-0.126	0.140	0.133	0.105	0.427	0.455	0.483	0.112	-0.420	-0.154	0.308	0.538	0.531	0.671	0.594	0.476
Dec NG	0.392	0.671	0.007	0.217	0.154	0.168	0.483	0.476	0.469	0.112	-0.350	-0.091	0.266	0.490	0.476	0.636	0.559	0.490

**Figure A-1: Historical Rank Correlation Matrix**

	Mar Com	May Com	July Com	Sep Com	Dec Com	Mar+1 Com	Jan+1 Uhl	Feb+1 Uhl	Mar+1 Uhl	Apr Uhl	May Uhl	June Uhl	July Uhl	Aug Uhl	Sep Uhl	Oct Uhl	Nov Uhl	Dec Uhl	Jan+1 NG
Mar Com	1.000	0.310	-0.117	-0.110	-0.176	-0.164	0.101	0.101	0.101	0.101	0.101	0.101	0.101	0.101	0.101	0.101	0.101	0.101	0.301
May Com	0.310	1.000	0.580	0.328	0.322	0.334	0.101	0.101	0.101	0.101	0.101	0.101	0.101	0.101	0.101	0.101	0.101	0.101	0.301
July Com	-0.117	0.580	1.000	0.774	0.597	0.686	0.101	0.101	0.101	0.101	0.101	0.101	0.101	0.101	0.101	0.101	0.101	0.101	0.301
Sep Com	-0.110	0.328	0.774	1.000	0.820	0.888	0.101	0.101	0.101	0.101	0.101	0.101	0.101	0.101	0.101	0.101	0.101	0.101	0.301
Dec Com	-0.176	0.322	0.597	0.820	1.000	0.848	0.101	0.101	0.101	0.101	0.101	0.101	0.101	0.101	0.101	0.101	0.101	0.101	0.301
Mar+1 Com	-0.164	0.334	0.686	0.888	0.848	1.000	0.101	0.101	0.101	0.101	0.101	0.101	0.101	0.101	0.101	0.101	0.101	0.101	0.301
Jan+1 Uhl	0.101	0.101	0.101	0.101	0.101	0.101	1.000	0.659	0.607	0.246	0.298	0.349	0.401	0.452	0.504	0.556	0.607	0.659	0.304
Feb+1 Uhl	0.101	0.101	0.101	0.101	0.101	0.101	0.659	1.000	0.659	0.195	0.246	0.298	0.349	0.401	0.452	0.504	0.556	0.607	0.304
Mar+1 Uhl	0.101	0.101	0.101	0.101	0.101	0.101	0.607	0.659	1.000	0.143	0.195	0.246	0.298	0.349	0.401	0.452	0.504	0.556	0.304
Apr Uhl	0.101	0.101	0.101	0.101	0.101	0.101	0.246	0.195	0.143	1.000	0.659	0.607	0.556	0.504	0.452	0.401	0.349	0.298	0.304
May Uhl	0.101	0.101	0.101	0.101	0.101	0.101	0.298	0.246	0.195	0.659	1.000	0.659	0.607	0.556	0.504	0.452	0.401	0.349	0.304
June Uhl	0.101	0.101	0.101	0.101	0.101	0.101	0.349	0.298	0.246	0.607	0.659	1.000	0.659	0.607	0.556	0.504	0.452	0.401	0.304
July Uhl	0.101	0.101	0.101	0.101	0.101	0.101	0.401	0.349	0.298	0.556	0.607	0.659	1.000	0.659	0.607	0.556	0.504	0.452	0.304
Aug Uhl	0.101	0.101	0.101	0.101	0.101	0.101	0.452	0.401	0.349	0.504	0.556	0.607	0.659	1.000	0.659	0.607	0.556	0.504	0.304
Sep Uhl	0.101	0.101	0.101	0.101	0.101	0.101	0.504	0.452	0.401	0.452	0.504	0.556	0.607	0.659	1.000	0.659	0.607	0.556	0.304
Oct Uhl	0.101	0.101	0.101	0.101	0.101	0.101	0.556	0.504	0.452	0.401	0.452	0.504	0.556	0.607	0.659	1.000	0.659	0.607	0.304
Nov Uhl	0.101	0.101	0.101	0.101	0.101	0.101	0.607	0.556	0.504	0.349	0.401	0.452	0.504	0.556	0.607	0.659	1.000	0.659	0.304
Dec Uhl	0.101	0.101	0.101	0.101	0.101	0.101	0.659	0.607	0.556	0.298	0.349	0.401	0.452	0.504	0.556	0.607	0.659	1.000	0.304
Jan+1 NG	0.301	0.301	0.301	0.301	0.301	0.301	0.304	0.304	0.304	0.304	0.304	0.304	0.304	0.304	0.304	0.304	0.304	0.304	1.000
Feb+1 NG	0.301	0.301	0.301	0.301	0.301	0.301	0.304	0.304	0.304	0.304	0.304	0.304	0.304	0.304	0.304	0.304	0.304	0.304	0.795
Mar+1 NG	0.301	0.301	0.301	0.301	0.301	0.301	0.304	0.304	0.304	0.304	0.304	0.304	0.304	0.304	0.304	0.304	0.304	0.304	0.770
Apr NG	0.301	0.301	0.301	0.301	0.301	0.301	0.304	0.304	0.304	0.304	0.304	0.304	0.304	0.304	0.304	0.304	0.304	0.304	0.601
May NG	0.301	0.301	0.301	0.301	0.301	0.301	0.304	0.304	0.304	0.304	0.304	0.304	0.304	0.304	0.304	0.304	0.304	0.304	0.625
June NG	0.301	0.301	0.301	0.301	0.301	0.301	0.304	0.304	0.304	0.304	0.304	0.304	0.304	0.304	0.304	0.304	0.304	0.304	0.650
July NG	0.301	0.301	0.301	0.301	0.301	0.301	0.304	0.304	0.304	0.304	0.304	0.304	0.304	0.304	0.304	0.304	0.304	0.304	0.674
Aug NG	0.301	0.301	0.301	0.301	0.301	0.301	0.304	0.304	0.304	0.304	0.304	0.304	0.304	0.304	0.304	0.304	0.304	0.304	0.698
Sep NG	0.301	0.301	0.301	0.301	0.301	0.301	0.304	0.304	0.304	0.304	0.304	0.304	0.304	0.304	0.304	0.304	0.304	0.304	0.722
Oct NG	0.301	0.301	0.301	0.301	0.301	0.301	0.304	0.304	0.304	0.304	0.304	0.304	0.304	0.304	0.304	0.304	0.304	0.304	0.746
Nov NG	0.301	0.301	0.301	0.301	0.301	0.301	0.304	0.304	0.304	0.304	0.304	0.304	0.304	0.304	0.304	0.304	0.304	0.304	0.770
Dec NG	0.301	0.301	0.301	0.301	0.301	0.301	0.304	0.304	0.304	0.304	0.304	0.304	0.304	0.304	0.304	0.304	0.304	0.304	0.795

**Figure A-2: Target Rank Correlation Matrix**



	May Com	July Com	Sep Com	Dec Com	Mar+1 Com	Jan+1 Uhl	Feb+1 Uhl	Mar+1 Uhl	Apr Uhl	May Uhl	June Uhl	July Uhl	Aug Uhl	Sep Uhl	Oct Uhl	Nov Uhl	Dec Uhl	Jan NG	Feb NG	Mar NG
May Com	1.000	0.561	0.310	0.308	0.319	0.095	0.099	0.096	0.095	0.098	0.102	0.100	0.099	0.098	0.096	0.094	0.096	0.288	0.291	0.288
July Com	0.561	1.000	0.760	0.582	0.670	0.099	0.093	0.092	0.091	0.093	0.094	0.098	0.097	0.098	0.094	0.091	0.092	0.283	0.285	0.283
Sep Com	0.310	0.760	1.000	0.803	0.878	0.103	0.099	0.097	0.093	0.095	0.096	0.098	0.101	0.108	0.102	0.103	0.098	0.279	0.286	0.283
Dec Com	0.308	0.582	0.803	1.000	0.831	0.096	0.095	0.098	0.094	0.093	0.096	0.099	0.098	0.108	0.099	0.101	0.090	0.283	0.286	0.285
Mar+1 Com	0.319	0.670	0.878	0.831	1.000	0.098	0.100	0.100	0.094	0.096	0.095	0.100	0.101	0.109	0.102	0.102	0.098	0.281	0.285	0.283
Jan+1 Uhl	0.095	0.099	0.103	0.096	0.098	1.000	0.641	0.591	0.233	0.290	0.342	0.387	0.439	0.492	0.534	0.584	0.644	0.295	0.293	0.296
Feb+1 Uhl	0.099	0.093	0.099	0.095	0.100	0.641	1.000	0.639	0.184	0.237	0.291	0.337	0.362	0.442	0.487	0.534	0.563	0.293	0.298	0.297
Mar+1 Uhl	0.096	0.092	0.097	0.098	0.100	0.591	0.639	1.000	0.138	0.188	0.238	0.292	0.341	0.393	0.439	0.489	0.539	0.288	0.292	0.292
Apr Uhl	0.095	0.091	0.093	0.094	0.094	0.233	0.184	0.138	1.000	0.638	0.585	0.537	0.480	0.426	0.386	0.326	0.285	0.292	0.295	0.290
May Uhl	0.098	0.093	0.095	0.093	0.096	0.290	0.237	0.188	0.638	1.000	0.641	0.592	0.538	0.483	0.441	0.385	0.332	0.300	0.302	0.298
June Uhl	0.102	0.094	0.096	0.096	0.095	0.342	0.291	0.238	0.585	0.641	1.000	0.643	0.587	0.541	0.492	0.437	0.388	0.303	0.299	0.300
July Uhl	0.100	0.098	0.098	0.099	0.100	0.387	0.337	0.292	0.537	0.592	0.643	1.000	0.640	0.590	0.540	0.483	0.430	0.292	0.293	0.294
Aug Uhl	0.099	0.097	0.101	0.098	0.101	0.439	0.362	0.341	0.480	0.538	0.587	0.640	1.000	0.641	0.593	0.542	0.490	0.298	0.298	0.298
Sep Uhl	0.098	0.098	0.108	0.108	0.109	0.492	0.442	0.393	0.426	0.483	0.541	0.590	0.641	1.000	0.644	0.586	0.540	0.296	0.294	0.295
Oct Uhl	0.096	0.094	0.102	0.099	0.102	0.534	0.487	0.439	0.386	0.441	0.492	0.540	0.593	0.644	1.000	0.643	0.592	0.296	0.295	0.295
Nov Uhl	0.094	0.091	0.103	0.101	0.102	0.584	0.534	0.489	0.326	0.385	0.437	0.483	0.542	0.586	0.643	1.000	0.636	0.294	0.291	0.294
Dec Uhl	0.096	0.092	0.098	0.090	0.098	0.644	0.593	0.539	0.285	0.332	0.388	0.430	0.490	0.540	0.592	0.636	1.000	0.290	0.294	0.292
Jan NG	0.288	0.283	0.279	0.283	0.281	0.295	0.293	0.288	0.292	0.300	0.303	0.292	0.298	0.296	0.296	0.294	0.290	1.000	0.783	0.757
Feb NG	0.291	0.285	0.286	0.286	0.285	0.293	0.298	0.292	0.295	0.302	0.299	0.293	0.298	0.294	0.295	0.291	0.294	0.783	1.000	0.781
Mar NG	0.288	0.283	0.283	0.285	0.283	0.296	0.297	0.292	0.290	0.298	0.300	0.294	0.298	0.295	0.295	0.294	0.292	0.757	0.781	1.000
Apr NG	0.293	0.285	0.281	0.284	0.285	0.290	0.289	0.288	0.292	0.291	0.292	0.287	0.294	0.291	0.287	0.282	0.281	0.584	0.562	0.536
May NG	0.290	0.286	0.285	0.285	0.285	0.290	0.286	0.286	0.291	0.296	0.295	0.291	0.291	0.292	0.290	0.283	0.283	0.603	0.581	0.557
June NG	0.289	0.286	0.285	0.287	0.288	0.293	0.289	0.288	0.290	0.298	0.298	0.293	0.298	0.299	0.292	0.285	0.285	0.631	0.606	0.583
July NG	0.288	0.284	0.282	0.286	0.286	0.293	0.291	0.288	0.292	0.301	0.297	0.293	0.298	0.300	0.294	0.286	0.292	0.654	0.634	0.604
Aug NG	0.288	0.282	0.282	0.288	0.285	0.295	0.296	0.292	0.290	0.300	0.296	0.288	0.290	0.297	0.292	0.288	0.286	0.683	0.658	0.632
Sep NG	0.287	0.286	0.284	0.284	0.285	0.294	0.297	0.290	0.296	0.300	0.298	0.292	0.297	0.297	0.296	0.290	0.286	0.701	0.681	0.655
Oct NG	0.294	0.283	0.278	0.281	0.281	0.294	0.293	0.290	0.296	0.301	0.297	0.292	0.294	0.294	0.293	0.291	0.287	0.729	0.705	0.681
Nov NG	0.290	0.286	0.286	0.288	0.286	0.295	0.294	0.287	0.292	0.298	0.296	0.289	0.293	0.294	0.295	0.290	0.289	0.755	0.730	0.707
Dec NG	0.289	0.280	0.281	0.281	0.280	0.292	0.294	0.287	0.291	0.297	0.297	0.289	0.293	0.292	0.292	0.288	0.288	0.779	0.758	0.732

**Figure A-3: Rank Correlation Matrix of Simulated Prices**

	May Com	July Com	Sep Com	Dec Com	Mar+1 Com	Jan+1 Uhl	Feb+1 Uhl	Mar+1 Uhl	Apr Uhl	May Uhl	June Uhl	July Uhl	Aug Uhl	Sep Uhl	Oct Uhl	Nov Uhl	Dec Uhl	Jan NG	Feb NG	Mar NG
May Com	0.000	-0.019	-0.018	-0.014	-0.015	-0.006	-0.002	-0.005	-0.006	-0.003	0.001	-0.001	-0.002	-0.003	-0.005	-0.007	-0.005	-0.013	-0.010	-0.013
July Com	-0.019	0.000	-0.014	-0.015	-0.016	-0.002	-0.008	-0.009	-0.010	-0.008	-0.007	-0.003	-0.004	-0.003	-0.007	-0.010	-0.009	-0.018	-0.016	-0.018
Sep Com	-0.018	-0.014	0.000	-0.017	-0.010	0.002	-0.002	-0.004	-0.008	-0.006	-0.005	-0.003	0.000	0.007	0.001	0.002	-0.003	-0.022	-0.015	-0.018
Dec Com	-0.014	-0.015	-0.017	0.000	-0.017	-0.006	-0.006	-0.003	-0.007	-0.008	-0.005	-0.002	-0.003	0.007	-0.002	0.000	-0.011	-0.018	-0.015	-0.016
Mar+1 Com	-0.015	-0.016	-0.010	-0.017	0.000	-0.003	-0.001	-0.001	-0.007	-0.005	-0.006	-0.001	0.000	0.008	0.001	0.001	-0.003	-0.020	-0.016	-0.018
Jan+1 Uhl	-0.006	-0.002	0.002	-0.005	-0.003	0.000	-0.018	-0.016	-0.013	-0.008	-0.007	-0.014	-0.013	-0.012	-0.022	-0.023	-0.015	-0.009	-0.011	-0.008
Feb+1 Uhl	-0.002	-0.008	-0.002	-0.006	-0.001	-0.018	0.000	-0.020	-0.011	-0.009	-0.007	-0.012	-0.009	-0.010	-0.017	-0.022	-0.014	-0.011	-0.006	-0.007
Mar+1 Uhl	-0.005	-0.009	-0.004	-0.003	-0.001	-0.016	-0.020	0.000	-0.005	-0.007	-0.008	-0.006	-0.008	-0.008	-0.013	-0.015	-0.017	-0.016	-0.012	-0.012
Apr Uhl	-0.006	-0.010	-0.008	-0.007	-0.007	-0.013	-0.011	-0.005	0.000	-0.021	-0.022	-0.019	-0.024	-0.026	-0.015	-0.023	-0.013	-0.012	-0.009	-0.014
May Uhl	-0.003	-0.008	-0.006	-0.008	-0.005	-0.008	-0.009	-0.007	-0.021	0.000	-0.018	-0.015	-0.018	-0.021	-0.011	-0.016	-0.017	-0.004	-0.002	-0.006
June Uhl	0.001	-0.007	-0.005	-0.005	-0.006	-0.007	-0.007	-0.008	-0.022	-0.018	0.000	-0.016	-0.020	-0.015	-0.012	-0.015	-0.013	-0.001	-0.005	-0.004
July Uhl	-0.001	-0.003	-0.003	-0.002	-0.001	-0.014	-0.012	-0.006	-0.019	-0.015	-0.016	0.000	-0.019	-0.017	-0.016	-0.021	-0.022	-0.012	-0.011	-0.010
Aug Uhl	-0.002	-0.004	0.000	-0.003	0.000	-0.013	-0.009	-0.008	-0.024	-0.018	-0.020	-0.019	0.000	-0.018	-0.014	-0.014	-0.014	-0.006	-0.006	-0.006
Sep Uhl	-0.003	-0.003	0.007	0.007	0.008	-0.012	-0.010	-0.008	-0.026	-0.021	-0.015	-0.017	-0.018	0.000	-0.015	-0.021	-0.016	-0.008	-0.010	-0.009
Oct Uhl	-0.005	-0.007	0.001	-0.002	0.001	-0.022	-0.017	-0.013	-0.015	-0.011	-0.012	-0.016	-0.014	-0.015	0.000	-0.016	-0.015	-0.008	-0.009	-0.009
Nov Uhl	-0.007	-0.010	0.002	0.000	0.001	-0.023	-0.022	-0.015	-0.023	-0.016	-0.015	-0.021	-0.014	-0.021	-0.016	0.000	-0.023	-0.010	-0.013	-0.010
Dec Uhl	-0.005	-0.009	-0.003	-0.011	-0.003	-0.015	-0.014	-0.017	-0.013	-0.017	-0.013	-0.022	-0.014	-0.016	-0.015	-0.023	0.000	-0.014	-0.010	-0.012
Jan NG	-0.013	-0.018	-0.022	-0.018	-0.020	-0.009	-0.011	-0.016	-0.012	-0.004	-0.001	-0.012	-0.006	-0.008	-0.008	-0.010	-0.014	0.000	-0.012	-0.013
Feb NG	-0.010	-0.016	-0.015	-0.015	-0.016	-0.011	-0.006	-0.012	-0.009	-0.002	-0.005	-0.011	-0.006	-0.010	-0.009	-0.013	-0.010	-0.012	0.000	-0.014
Mar NG	-0.013	-0.018	-0.018	-0.016	-0.018	-0.008	-0.007	-0.012	-0.014	-0.006	-0.004	-0.010	-0.006	-0.009	-0.009	-0.010	-0.012	-0.013	-0.014	0.000
Apr NG	-0.008	-0.016	-0.020	-0.017	-0.016	-0.014	-0.015	-0.016	-0.012	-0.013	-0.012	-0.017	-0.010	-0.013	-0.017	-0.022	-0.023	-0.017	-0.015	-0.017
May NG	-0.011	-0.015	-0.016	-0.016	-0.016	-0.014	-0.018	-0.018	-0.013	-0.008	-0.009	-0.013	-0.013	-0.012	-0.014	-0.021	-0.021	-0.022	-0.020	-0.020
June NG	-0.012	-0.015	-0.016	-0.014	-0.013	-0.011	-0.015	-0.016	-0.014	-0.006	-0.006	-0.011	-0.006	-0.005	-0.012	-0.019	-0.019	-0.019	-0.019	-0.018
July NG	-0.013	-0.017	-0.019	-0.015	-0.015	-0.011	-0.013	-0.016	-0.012	-0.003	-0.007	-0.011	-0.006	-0.004	-0.010	-0.018	-0.012	-0.020	-0.016	-0.021
Aug NG	-0.013	-0.019	-0.019	-0.013	-0.016	-0.009	-0.008	-0.012	-0.014	-0.004	-0.008	-0.016	-0.014	-0.007	-0.012	-0.016	-0.018	-0.015	-0.016	-0.018
Sep NG	-0.014	-0.015	-0.017	-0.017	-0.016	-0.010	-0.007	-0.014	-0.008	-0.004	-0.006	-0.012	-0.007	-0.007	-0.008	-0.014	-0.018	-0.021	-0.017	-0.019
Oct NG	-0.007	-0.018	-0.023	-0.020	-0.020	-0.010	-0.011	-0.014	-0.008	-0.003	-0.007	-0.012	-0.010	-0.010	-0.011	-0.013	-0.017	-0.017	-0.017	-0.017
Nov NG	-0.011	-0.015	-0.015	-0.013	-0.015	-0.009	-0.010	-0.017	-0.012	-0.006	-0.008	-0.015	-0.011	-0.010	-0.009	-0.014	-0.015	-0.015	-0.016	-0.015
Dec NG	-0.012	-0.021	-0.020	-0.020	-0.021	-0.012	-0.010	-0.017	-0.013	-0.007	-0.007	-0.015	-0.011	-0.012	-0.012	-0.016	-0.016	-0.016	-0.012	-0.014

**Figure A-4: Differences Between Target and Actual Rank Correlations**

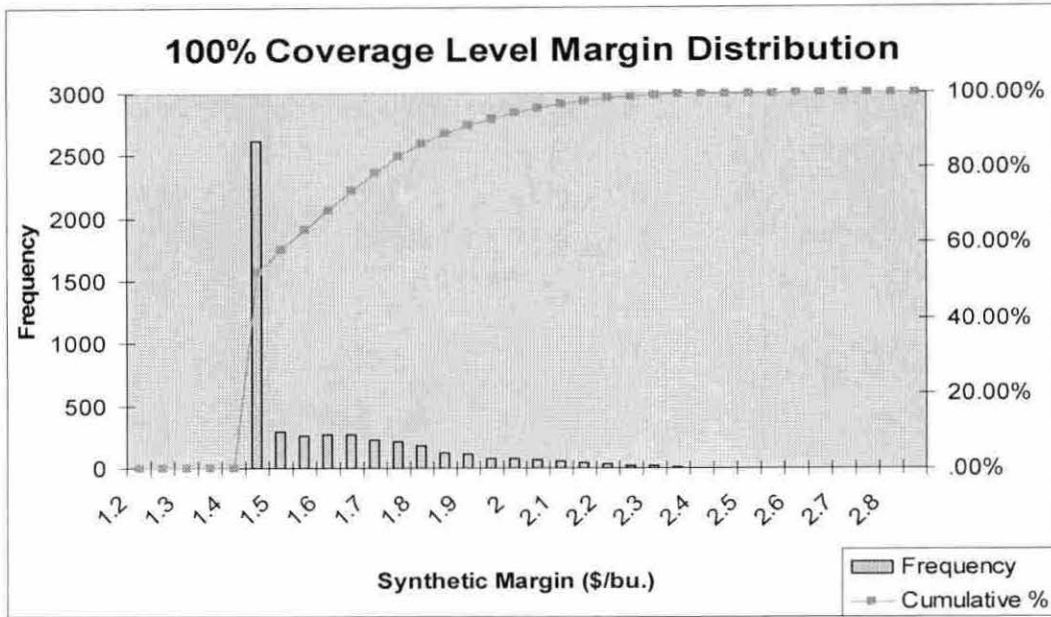


Figure A-5: Distribution of Gross Margins (\$/bu) at 100% Coverage-LEVEL

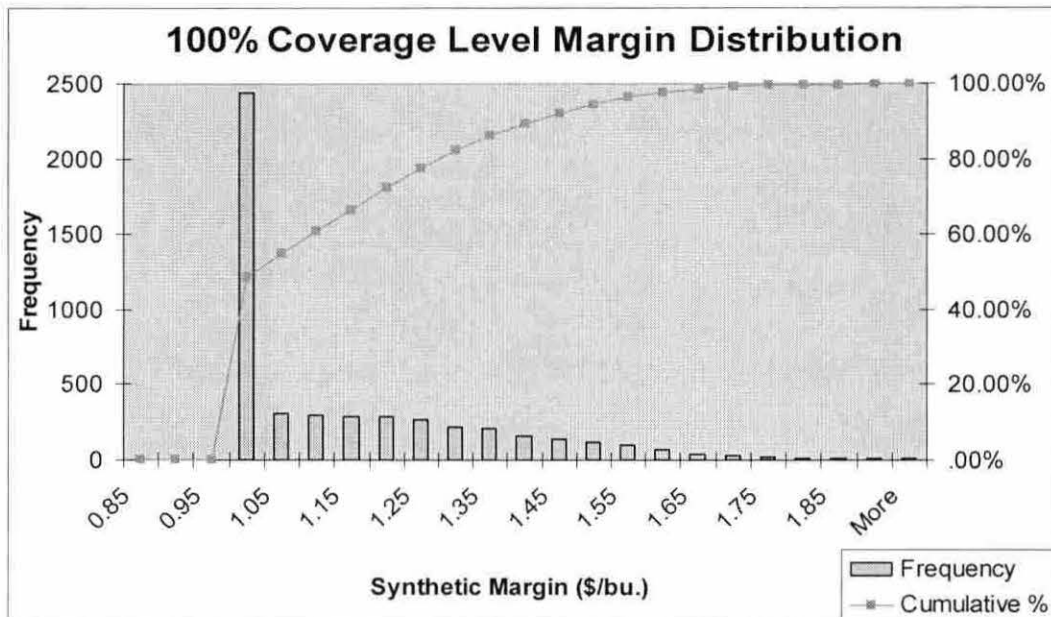


Figure A-6: Distribution of Gross Margins (\$/bu) at 100% Coverage-DIFF

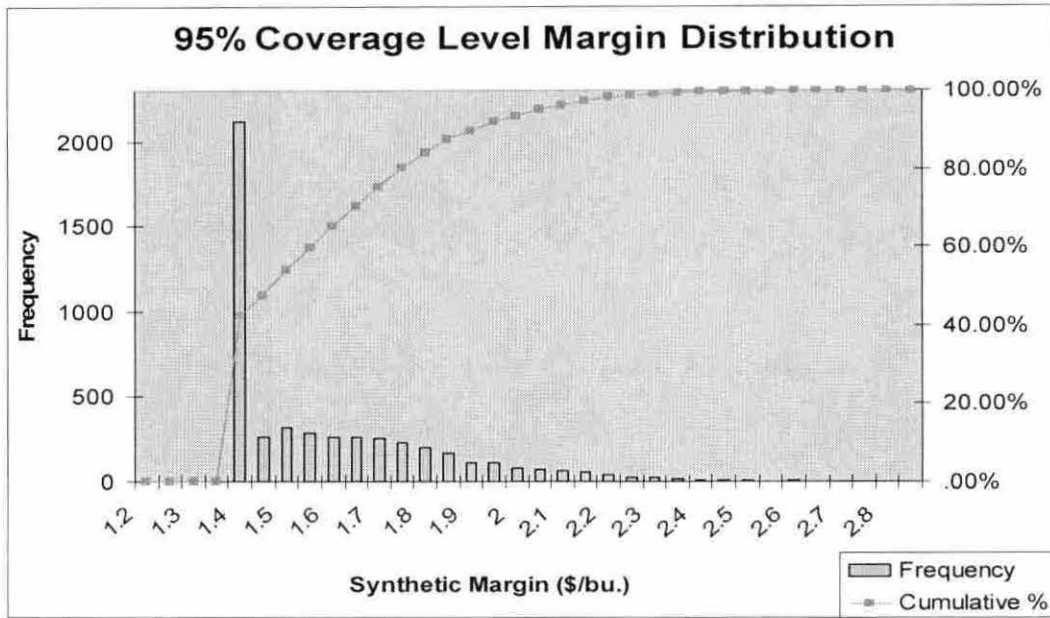


Figure A-7: Distribution of Gross Margins (\$/bu) at 95% Coverage-LEVEL

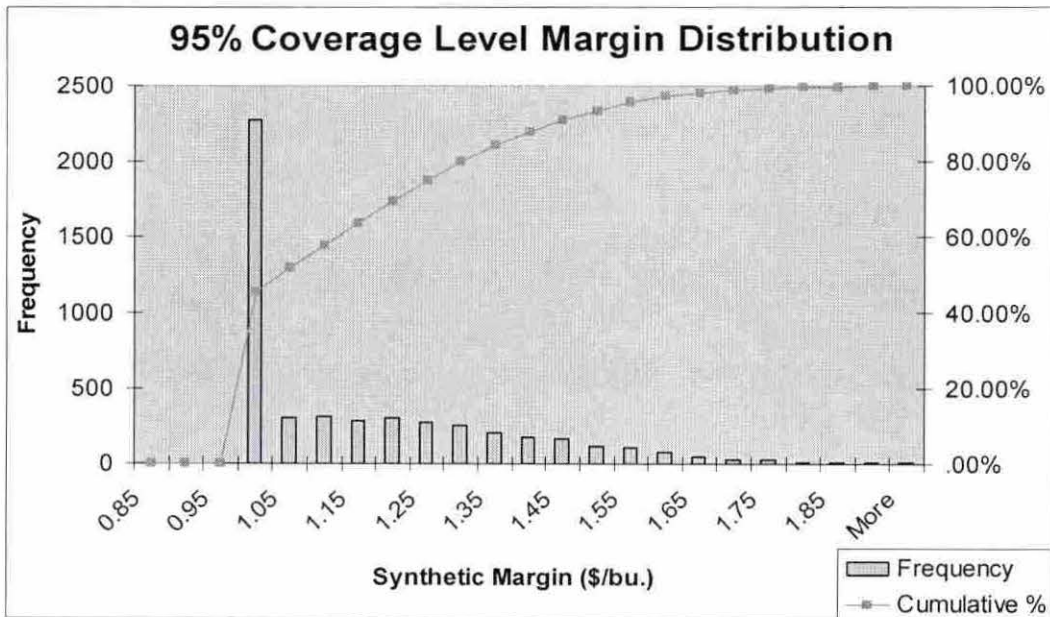


Figure A-8: Distribution of Gross Margins (\$/bu) at 95% Coverage-DIFF

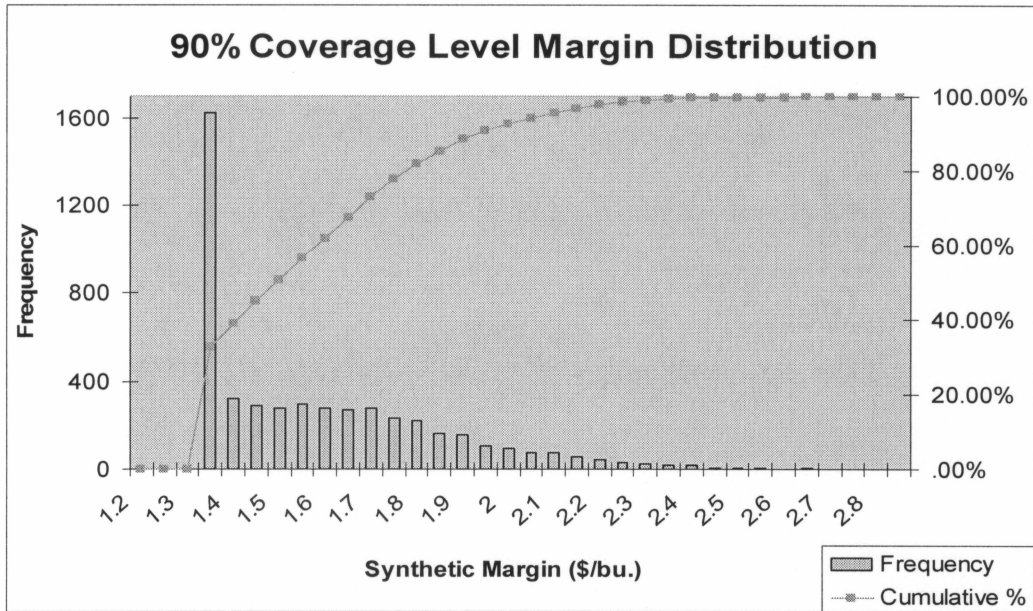


Figure A-9: Distribution of Gross Margins (\$/bu) at 90% Coverage-LEVEL

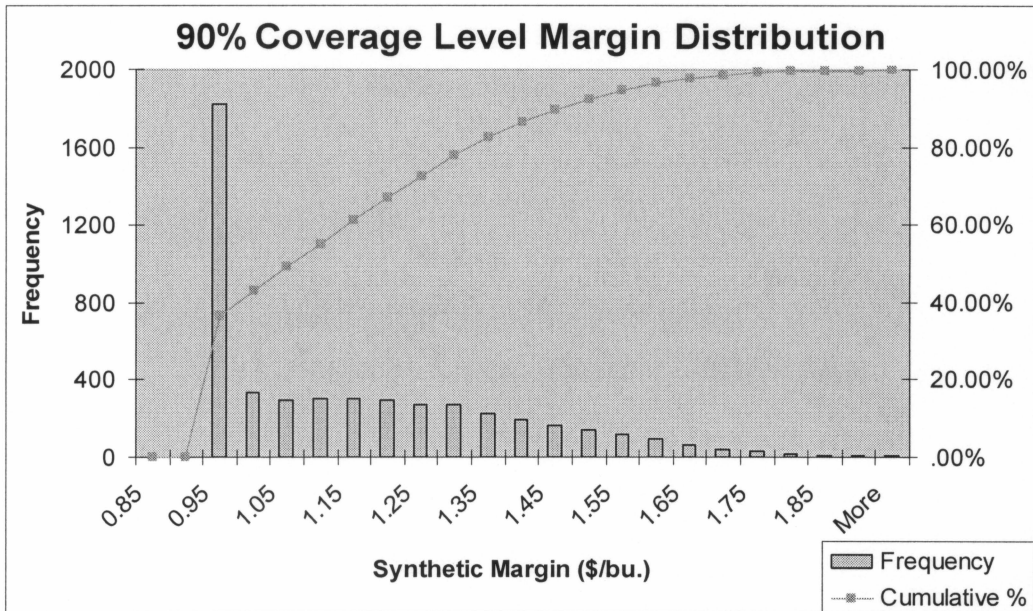


Figure A-10: Distribution of Gross Margins (\$/bu) at 90% Coverage-DIFF

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