VALUE-AT-RISK

AND ITS APPLICATION IN CATTLE FEEDING MANAGEMENT

by

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STATEMENT BY AUTHOR

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DEDICATION

To My Parents.

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ABSTRACT

The risk measurement technique known as Value-at-Risk (VaR) has recently become a standard approach for measuring the market risk of financial and commodity derivatives. With the bankruptcy of the Baring bank and other financial banking crises, VaR has been the focus to aide as a financial management tool. VaR also has potential to help in assessing risks for an agricultural enterprise. This study provides a "state-of-the-art" review of VaR estimation techniques and presents an empirical application for a cattle feeding operation. Different estimation techniques like historical moving averages, RiskMetrics, GARCH, and implied volatilities are deployed in predicting losses associated with cattle feeding margins. Results show that these techniques provide well-calibrated estimates of VaR such that violations (actual losses exceeding the VaR estimate) are commensurate with the desired level of confidence. In particular, estimates developed using J.P. Morgan's RiskMetrics™ methodology appear most robust for a linear payoff series such as cash commodity prices.

Chapter One

Introduction

1.1 Motivation

The concept of Value at Risk (VaR) is not new today. With the bankruptcy of Baring Bank in 1995 and the following huge losses suffered by Daiwa Bank, financial institutions all around the world realized that the disaster was caused by a deficiency of effective risk management. So, in recent years, banking regulators took initiatives to improve the disclosure of the potential risks that are involved in their daily positions and their derivatives. The landmark Basle accord of 1995 provided authoritative steps toward tighter risk management. This accord sets minimum capital requirements that must be met by commercial banks to cope with credit risk and encourages central banks to use the VaR management model as a basis for required capital ratios. Thus, VaR is being officially promoted as a sound risk management practice. Although banks have long recognized that managing financial risks is the natural business of financial institutions, the adoption of VaR undoubtedly helps them systemize their risk management to allow them to deploy their capital more efficiently and improve their comparative advantage.

Agricultural management shares similar risk exposure to financial institutions and their products' price fluctuation of underlying derivatives (e.g. futures and options). This determines the necessity of putting VaR into a management system. In this study, we focus on an agricultural management operation of cattle feeding.

The cattle industry is a major economic industry for United States agriculture. In terms of gross cash receipts, cattle and calves represent the largest segment of American agriculture. In 1999, cattle marketings accounted for almost a quarter of the value of all agriculture sales and 42 percent of livestock and poultry markets. Cattle are produced by more than 1.2 million producers, in more states and regions of the country than any other commodity. Yet, during the last decade, the industry was characterized by great fluctuations in profits. This high volatility raises an obvious need for risk management.

High profit volatility is due to several factors, which can be broadly classified as production-specific or market-specific factors. As with every producer, cattle feeders bear the risk of unfavorable price movements in both input and output markets. The main inputs in the production process are feeder cattle and feed, usually corn and soybean meal, and the only output is fed cattle. Cash expenses associated with a feeder, corn, and soybean meal needed to produce one fed steer ($ per head), are described in Figure 1. This figure clearly shows that the primary cost component for a producer is the cost of the feeder animal, which is on average 6 times more than the cost of the next most important input, corn. Finally, the cost of soybean meal additive is less than 2% of the cost of feeder, which is the main reason that this study drops it as a part of market related input costs.

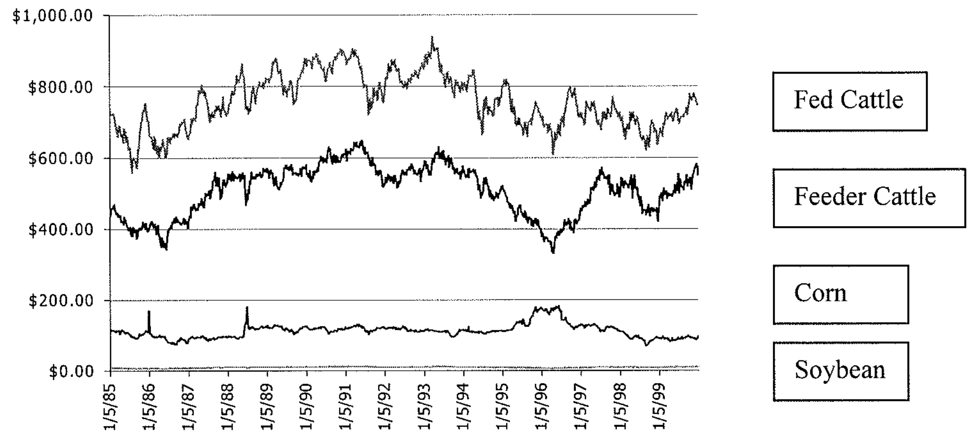

Figure 1. Gross Cash Expenses and Revenues

Source: Raw Data, Livestock Marketing Information Center

A considerable share of profit variability is explained by market price risks. For example, Trapp and Cleveland (1989) found that volatility of market prices for both fed and feeder cattle explained 65.5% of the production margin volatility, compared to 22% for production risk.

While profit fluctuations from production factors such as the cost of labor or cattle's response to weather changes are hard to anticipate and prevent, the component of production margin variance attributable to market price fluctuations can potentially be used to forecast future risk valuations.

The producer's gross feeding margin per head of fed cattle is shown in Figure 2 and the associated gross rate of return is represented in Figure 3. This is perhaps the most convincing argument why VaR estimation is important for a feedlot operation. Exhibiting

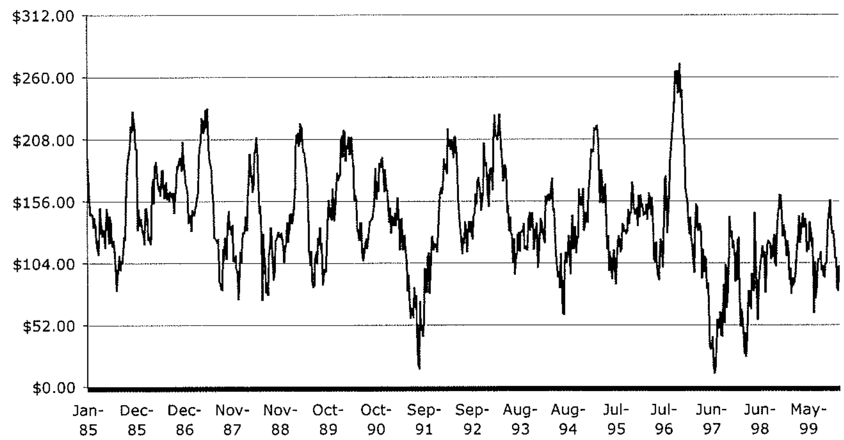

Figure 2. Gross Feeding Margin (Per Head)

Source: Raw Data, Livestock Marketing Information Center

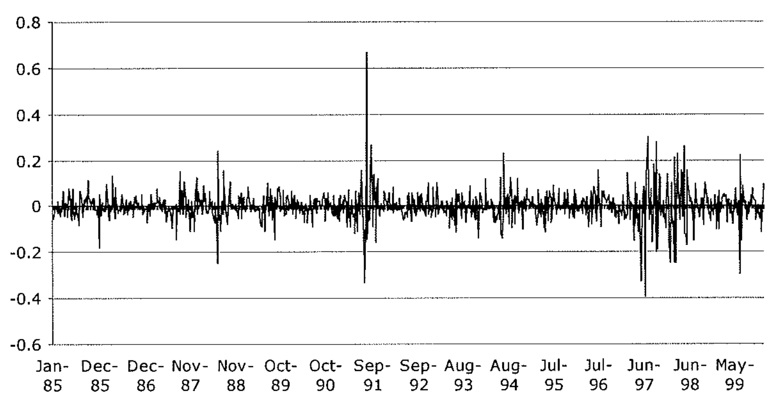

Figure 3. Gross Rate of Return

Source: Raw Data, Livestock Marketing Information Center

highly cyclical behavior, the margin varies from $270.87 per head to $15.45. While the graph serves its purpose of demonstrating the high variability of the gross feeding margin, the margins are not exact for reflecting absolute profits earned by producers due to variations in production performance and other production costs.

This research focuses on VaR estimates in the context of market risk variability factors for the cattle feeding margin. In particular, it develops different methods to estimate VaR for this industry and evaluates the outcome of the respective methods. While the theory has been widely discussed in the literature and applied to the financial management, it has not been applied to the cattle feeding industry. Subsequently, livestock risk management for the feed lot operation is the focus of this research.

Many people may question the applicability of VaR, since strategies have been adopted in cattle feeding management against market risks. Why is VaR important? The potential application of VaR in this industry not only helps managers disclose inherent risks, but also gives them information to make their financial decisions. Suppose a business wants to get a $500,000 loan from a bank with a fixed interest rate, how could VaR work in this scenario? First, the VaR of a current portfolio by investing this loan is calculated, then compared with the estimated VaR at a future time which coincides with the expiration date of the loan. If the future value is greater than the current one, which means there will be too much risk involved in this investment, a decision should be made to not obtain this loan. If the future value is smaller than the current one, take the loan. This rule can also be applied for stock investors. This is only one aspect of the VaR application, further discussions are presented in Chapter Five.

1.2 Organization

This paper develops as follows:

Chapter One gives an introduction of the motivation of this research. Due to price fluctuations inherent with cattle feeding, risk management will be the main focus for this thesis. Chapter Two supplies the literature review on the VaR concept and its methodology. Chapter Three explains the price data resources utilized for fed cattle, corn, and feeder cattle. Statistical merits of the models used to calculate VaR for feeder cattle are also discussed. Chapter Four presents empirical results of the different VaR estimation methods. Chapter Five gives concluding comments of the study.

Chapter Two

Theoretical Review of Value-at-Risk

2.1 Definition

VaR measures the worst portfolio losses over a given time period under normal market conditions at a specified confidence interval. For example, if the specified probability is 5 percent and the holding period is one day, then a value-at-risk of $1 million means that the daily mark-to-market loss will exceed $1 million with a probability of only 5 percent. In essence, VaR estimates attempt to capture extreme events that occur in the lower tail of the portfolio's return distributions. The major advantage of VaR relative to more traditional risk measures is its focus on downside risk. Consequently, VaR is praised for being an intuitive measure of risk and for its ability to capture the risks of many different assets into a single, concise number.

2.2 Theoretical Constructs of VaR

Jorion (1997) defines VaR for a general class of distributions such that the end-of-period portfolio value is $W=W_0(1+R)$, where W_0 is the initial investment value and R is the rate of return on the portfolio. Subsequently, Jorion (1997) defines the critical end-of-period portfolio value as W^*, where $W^*=W_0(1+R^*)$, W_0 is the initial investment and R^* is a critical level of portfolio return associated with a predetermined level of confidence(c). Therefore, W^* can be thought of as the end-of-period portfolio value when the worst possible portfolio return (R*) is realized, a return that one is unlikely to encounter more than 1-c percent of the time, where c is a specified confidence level, under normal market conditions.

In the most general form, VaR can be derived from the probability distribution of the future portfolio value *f(w)*. At a give confidence level c, we wish to find the worst possible realization, w* such that the probability of exceeding this value is c:

$$c = \int_{w^*}^{\infty} f(w)dw \qquad \textbf{(2.1)}$$

Or such that the probability of a value lower than W*, P=P (W≤W*) is 1-c:

$$1 - c = \int_{-\infty}^{w^*} f(w)dw = P(W \le W^*) = p = F(w) \qquad \textbf{(2.2)}$$

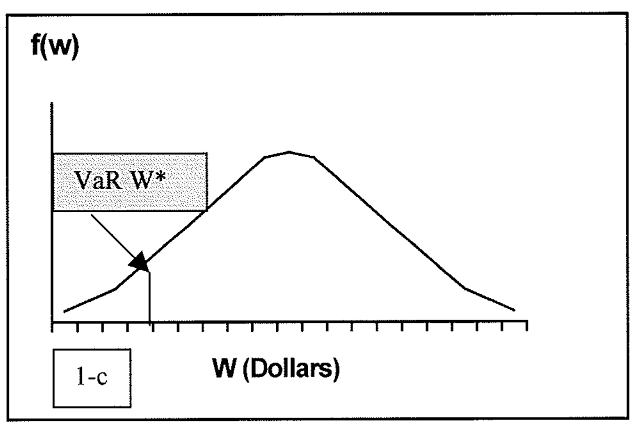

Figure 4. Illustration of Value-at-Risk

Source: Jorion (1997) *Value at Risk: The New Benchmark for Controlling Derivatives Risks* (p.90) where F is the cumulative density function, which is the area in the left tail of the distribution (see Figure 4). This area is associated with losses that are greater than or equal to the loss associated with confidence level (c) representing the downside risk, or VaR of the portfolio.

By assuming the general distribution of portfolio value, *f (w)* in Equation 2.1 is the standard normal distribution f (ε), where $\varepsilon \sim N(0,1)$. Normalizing R*-u (u is the sample mean), Jorion (1997) defines a normal deviate (α) as

$$-\alpha = \frac{-|R^*| - u}{\sigma} \tag{2.3}$$

Associating the normal deviate (α) with R*, Jorion shows that

$$1 - c = \int_{-\alpha}^{w^*} f(w)dw = \int_{-\alpha}^{-|R^*|} f(R)dR = \int_{-\infty}^{-\alpha} f(\varepsilon)d\varepsilon \tag{2.4}$$

From the equality in Equation 2.4, Jorion (1997, p.89) states that "the problem of Value-at-Risk is equivalent to finding the deviate α such that the area to the left of it is equal to 1-c." From the cumulative standard normal distribution, the confidence level c associated with the normal distribution is equal to 1.64485. Jorion notes that Equation 2.4 provides an illustrative linkage which shows that VaR may be found in terms of the portfolio value (W*), cutoff return (R*), or normal deviate (α). Therefore, VaR under the assumption of normality is

$$VaR_u = W_0 \alpha\sigma \tag{2.5}$$

where W_0 is defined as before to be the initial portfolio value, α equals the normal deviate associated with 1-c, and σ the standard deviation of portfolio returns. To find the VaR of a portfolio, one needs to multiply the estimated σ by the relevant α and initial investment. Obviously, under the assumption of normality, the only true unknown is the estimate of σ. Therefore, the problem becomes one of forecasting the volatility and correlations between individual assets and subsequent portfolio volatility.

2.3 VaR Estimations

Techniques used to generate VaR measures are not novel. VaR calculations are synonymous with forecasting the volatility of a portfolio over a particular holding period, paying special attention to the lower tail of the probability distribution. Two major classes of estimation procedures for VaR have received the most attention: parametric and full-valuation procedures. Parametric procedures determine estimates of volatility under the assumption of normality while full valuation procedures attempt to model the entire empirical return or revenue distribution. Despite the array of procedures that fall under each of these categories, there are many debates over the best method.

2.3.1 Parametric Estimates of VaR -The Delta-Normal Method

The Delta-Normal approach is based on the assumption that the underlying market factors (variables) have a multivariate normal distribution. As the portfolio return is a linear combination of normal variables, it is also normally distributed, since the portfolio return in the next period can be expressed as:

$$R_{p,t+1} = w_t` R_{i,t+1} w_t \tag{2.6}$$

where the weights w_t are indexed by time to recognize the dynamic nature of trading portfolios.

The portfolio variance can be calculated by

$$V\ (R_{p,t}) = w_t` \Sigma_{t+1} w_t \qquad (2.7)$$

Here, risk is generated by a combination of linear exposures to many factors that are assumed to be normally distributed and by the forecast of the covariance matrix $\Sigma_{t+1.}$ Within this class of models, two basic methods are generally used to measure the variance-covariance matrix. First, it can be based solely on historical data, using, for example, a model that allows for time variation in risk. Alternatively, it can include implied risk measures from the options trading markets, or a combination of both methods.

The use of parametric procedures for developing VaR measures under the assumption of normality has often been referred to as the delta-normal method. There is a well established and evolving body of literature focused on volatility forecasting in which the techniques can be adapted to VaR. For instance, historical volatility estimates, implied volatility from options prices, various conditional time series models (Jorion 1996, 1997; Hendricks 1996), and regime switching models (Duffie and Pan 1997; Venkataraman 1997). All have been suggested for use in delta-normal VaR. Much of the interest in parametric models of VaR has been motivated by the efforts of J.P. Morgan (1997) and the dissemination of their RiskMetrics methodology for developing estimates of standard deviation and correlation among portfolio assets using an exponentially weighted volatility measure. This has been widely researched and in general there is not much consensus as to their power to forecast volatility. However, the predominant consensus among academics is that implied volatility is the best forecast since it is the market's forecast of volatility. Due to the increasing interest in VaR, there is now added motivation for accurate volatility forecasts (Boudoukh, Richardson, and Whitelaw1997).

Delta-normal VaR has been praised for its ability to incorporate time-varying volatility through the use of GARCH models, using simple moving averages or exponentially weighted moving average such as J.P. Morgan's RiskMetrics™ procedures. Jorion (1997) claimed that parametric methods of VaR provide a superior forecast of downside risk for portfolios with little options content. In addition, Jorion (1996) praises

parametric methods for being less sensitive to estimation error in comparison to techniques that assume a general distribution. Linsmeier and Pearson (1996) maintain that the delta-normal method easily handles stress testing and scenario analysis by incorporating alternative variance/covariance relationships among various assets in a portfolio. Jorion (1997) also commends parametric methods for being easy to explain to management; however, Linsmeier and Pearson (1996); J.P. Morgan's RiskMetrics; and Mahoney (1996) stated the opposite. This would seem to be an issue solved on the basis of an individual manager's skill and familiarity with statistical methods.

The major criticism of delta-normal VaR relates to the assumption of normality of the return series used to construct volatility and correlation estimates. Since VaR attempts to explain information in the lower tail of a probability distribution, estimates of VaR can be distorted in the presence of leptokurtosis. However, Jorion (1996, 1997) suggests the use of alternative cumulative distribution, such as the student's t-distribution, when fat tails are encountered.

In fact, much of the VaR literature to date has focused on the problem of non-normality often found in financial data and the potential bias it can cause in delta-normal VaR models. The normality assumption also becomes problematic when a portfolio contains option positions, which can cause the return distribution to become skewed. To circumvent this problem, the incorporation of option gammas in addition to option deltas have been suggested as a way to represent the convexity of the option, acting as a proxy for the non-linear payoffs of options (Linsmeier and Pearson 1996; Jorion 1997; Ho, Chen and Eng 1996).

Another criticism of parametric VaR methods is that long horizon forecasts of VaR, beyond a one-day holding period, may fail to be accurate. The common practice to create long-horizon VaR forecasts is to use one-period ahead forecasts and extend the forecast to longer horizons by multiplying the one-period forecasts by the square root of the number of periods in the forecast horizon. However, according to Christoffersen and Diebold (1997, p.4), "Scaling is misleading and tends to produce spurious magnification of volatility. It is only valid under the assumption that returns are distributed *iid.*"

2.3.2 Full-Valuation Procedures

Full-valuation procedures that have been suggested for use in developing VaR estimates include simple historical simulation, full Monte Carlo simulation (Jorion 1997; Linsmeier and Pearson 1996), and bootstrapping methods (Jorion 1997; Duffie and Pan 1997). Full-valuation procedures, often called non-parametric VaR, attempt to model the entire return distribution instead of providing a point estimate of volatility.

The historical-simulation method provides a straightforward implementation of full valuation that requires relatively few assumptions about the statistical distributions of the underlying market factors. Basically, the approach involves applying the current weights to a time series of historical asset returns:

$$R_{P,T} = w_T{}' R_{i,T} w_T \qquad T = 1, 2, \ldots, t \qquad (2.8)$$

Note that the weights w_T are kept at their current values. This return does not represent an actual portfolio, but rather reconstructs the history of a hypothetical portfolio using the current position. The distribution of profits and losses is constructed by taking the current portfolio and subjecting it to the actual changes in the market factors experienced during each of the last T periods.

Hypothetical future prices for period T are obtained from applying historical changes in prices to the current level of prices:

$$P^*_{p,t} = P_{i,o} + \Delta P_{i,T} \qquad i = 1,2, \ldots, N \qquad (2.9)$$

A new portfolio value $P^*_{p,t}$ is then computed from the full set of hypothetical prices, perhaps incorporating nonlinear relationships. Note that, to capture the real risk, the set of prices can incorporate implied volatility measures. This creates the hypothetical return corresponding to observation T:

$$R_{p,T} = (P^*_{p,T} - P_{p,0}) / P_{p,0} \qquad (2.10)$$

VaR is then obtained from the entire distribution of hypothetical returns. Alternatively, one could assume normality and rely on the variance to compute the VaR. This provides more precise estimates of VaR as long as the actual distribution does not differ too much from normal.

The advantage of this method is that by relying on actual prices, the method allows nonlinearities and non-normal distributions. It does not rely on specific assumptions about valuation models or the underlying stochastic structure of the market. It accounts for "fat tails" and since it does not rely on valuation models, it is not prone to model risk. To improve the performance of the historical simulation method, however, Butler and Schachter (1997) propose a Kernel estimation procedure which provides a standard error of the estimated quantile that represents the VaR.

Despite the positive aspects of the historical simulation method, there are several drawbacks. Due to its reliance on historical data, long series of data are required and need continuous updating since more accurate distributions can only be approximated with larger periods of data (Mahoney 1996; Hendricks 1996). However, longer historical time periods present the possibility of picking up more extreme market moves associated with the tails of a probability distribution, potentially causing upward bias in the VaR estimate (Butler and Schachter 1997). Another major assumption behind the historical simulation method is that individual returns are distributed *iid*. The use of long data series to provide increased precision in VaR estimates may come at the expense of violating the *iid* assumption. Finally, the same weight is place on all observations, ignoring time variation of the variance of the distribution (Jorion 1997). In addition, quantiles estimated from full-valuation methods, according to Jorion (1996), are more prone to estimation error since they tend to have much larger standard errors than parametric methods, which use estimates of standard deviation.

The Monte Carlo simulation methodology has a number of similarities to historical simulation. The main difference is that rather than carrying out the simulation using the observed changes in market factors over the last T periods to generate T hypothetical portfolio profits or losses, one chooses a statistical distribution that is believed to adequately capture approximate changes in market factors. Then a pseudo-random number generator is used to generate thousands or perhaps tens of thousands of hypothetical changes in the market factors. These are then used to construct thousands of hypothetical portfolio profits and losses on the current portfolio, and the distribution of possible portfolio profit or loss. Finally, the value at risk is then determined from this distribution.

Jorion (1997) and Linsmeier and Pearson (1996) claim that Monte Carlo methods are the most flexible of VaR estimation techniques. They incorporate options content well and have distributional flexibility. However, the flexibility of Monte Carlo methods may also be its downfall. Jorion (1997) as well as Mahoney (1996), greatly criticize Monte Carlo methodology for estimating VaR since it is very prone to specification error, especially with a complex portfolio. The geometric Brownian motion process is used to describe the underlying data generating process. Time variation may be added through Generalized AutoRegressive Conditional Heteroskedasticity (GARCH) variance terms (Jorion 1997), however, time variation may be distorted with Monte Carlo methods, suggesting a trade-off between time and model flexibility. Ho, Chen and Eng (1996) are also critical of Monte Carlo methods, and full-valuation techniques in general, since these methods do not have the ability to obtain an explicit variance/covariance matrix in order to analyze the marginal contribution of an asset to overall portfolio risk. Also, management may find it difficult to understand Monte Carlo simulation methods.

As an alternative to pure Monte Carlo methods, Jorion (1997), Duffie and Pan (1997) discuss bootstrapping techniques for developing VaR estimates. Bootstrapping techniques are fundamentally similar to historical simulation but sample past returns with replacement in building the return distribution. According to Jorion (1997), bootstrapping techniques help to take into consideration fat-tailed distributions, but often at the expense of time variation, similar to historical simulation and Monte Carlo methods.

2.4 Empirical Evaluation of Alternative Value-at –Risk Models

The previous section outlined the pros and cons of various VaR estimation methods. There is, however, a growing literature of empirical studies that examined the performance of alternative VaR methodologies. Although many consider VaR to be synonymous with volatility forecasting, especially when using parametric methods, VaR is unique since it concentrates on downside risk and subsequently on the behavior of distribution tails.

Mahoney examined the performance of a simplistic full-valuation VaR model (the historical simulation method) versus two parametric models that assumed returns were normally distributed. The parametric methods examined were the exponential moving average model advocated by J.P. Morgan and an equally weighted historical moving average forecast. Using a 1,000-day rolling sample of randomly drawn portfolios of currency exchange rates and foreign equity index data, Mahoney (1996) found that VaR estimates computed from the historical simulation method were more representative of actual portfolio losses than either of two parametric methods evaluated for high levels of confidence (greater than 95%). He found that the historical simulation method modeled the entire distribution more appropriately than parametric methods, in particular the extreme tails of the distribution. For the parametric methods, however, Mahoney (1996) found that they were very biased for high confidence level (>99%) in that they "understated the frequency of large downward movements in portfolio values" (p.214). This bias was more severe with the equity portfolios than with the exchange rate portfolio, illustrating that performance of VaR estimates are potentially sensitive to the data series analyzed. However, for exchange rate data, the parametric methods provided unbiased VaR estimates at lower levels of confidence (90% and 95%).

Using similar data and methods to that of Mahoney (1996), Hendricks (1996) compared several parametric and full valuation methods of VaR to the random exchange rate portfolio. For the parametric methods, Hendricks (1996) used exponential moving averages incorporating 3 different decay weights and various estimation windows for the equally weighted moving average ranging from 50 to 1,250 days. For the historical simulation method, windows of 125, 250, 500 and 1,250 days were used. Based on several evaluation criteria, Hendricks (1996) generally concluded that all VaR estimates measured the risk that they were intended to cover, in particular at the 95% level. Hendricks (1996) did note that the J.P. Morgan approach (exponential moving average) picked up the time-varying nature of the sample series and that longer holding periods produced more accurate results despite being more volatile over time. Similar to

Mahoney (1996), he did find that the majority of models performed poorly at the 99% level of confidence and that "accurate estimates of extreme percentiles require the use of long periods" (Hendricks 1996, p.50). In addition, he found that the historical simulation method produced a positive upward biased VaR estimate relative to the average of the alternative VaR estimates, not to the realized risk.

Hendricks (1996) also found that when VaR was violated, the magnitude of the violation was quite large, contributing to the leptokurtosis of the actual return distribution. Overall, Hendricks (1996, p.56) concluded, "although we cannot recommend any single Value-at-Risk approach, our results suggest that further research aimed at combining the best features of the approaches examined here may be worthwhile."

In response to observed leptokurtosis in several financial return series, Venkataraman (1997) suggested and tested the use of a "mixture of normal" technique utilizing a quasi-Baysian maximum likelihood (QB-MLE) procedure to account for the leptokurtosis often identified with financial time series. Modeling several currency positions, Venkataraman (1997) found that the mixtures of normal approach performed better than models that assumed normality for both individual currency positions and for a random portfolio of currencies. However, Venkataraman (1997) did not test the QB-MLE procedure against commonly used VaR estimators such as the exponential moving average technique advocated by J.P. Morgan's RiskMetrics or procedures that take into consideration potential time variation which is often linked to causing leptokurtosis.

Also addressing the issue of observed leptokurtosis in financial assets, Green, Matin and Pearson (1996) examined robust estimation techniques applied to traditional standard deviation and correlation estimates in the context of VaR. They stated that "outliers tend to cause a positive bias in the standard deviation estimate" (p.192) and therefore result in VaR estimates that are too conservative. This is contrary to other studies that concluded fat-tailed distributions tend to underestimate VaR (Mahoney 1996; Hendricks 1996). Despite the ability of robust estimates to reduce the effects of leptokurtosis, Green, Matin and Pearson (1996) were critical of robust techniques since they tended to underestimate actual risks, thus creating a new bias in the estimates.

Beder (1995) compared alternative full-valuation procedures for calculating the VaR of portfolios for Treasury strips and equity index positions. Contrary to Mahoney (1996) and Hendricks (1996), Beder (1995) was highly critical of all VaR models tested in her study. For both one-day and two-week holding periods, results showed drastic differences in VaR estimates across alternative full-valuation estimation procedures for the various portfolios examined. Differences among models were even greater when non-linear positions were included in the portfolio. Beder (1995) was adamant in the view that risk measurement using VaR is not a panacea for good risk management practices. However, Beder (1995) failed to test the various out-of-sample estimates in order to discern which of the alternative full-valuation techniques was superior for the hypothetical portfolios. This study focused more on the magnitude of errors stemming from different methods than on performance evaluation among models of the study for a particular procedure.

Jackson, Maude, and Perraudin (1997) were unique in that they examined real portfolios held by a bank in contrast to a single asset or randomly selected portfolios of assets such as the studies of Mahoney (1996), Hendricks (1996), and Beder (1995). As they noted: "Studies that analyze VaR modeling on the basis of, for example, a single equity index of foreign exchange rate seem to us to be ill-advised. Therefore, it is important to look at realistic portfolios." (Jackson, Maude, and Perraudin, p.87). The portfolios they examined were for foreign equity and exchange rate positions. Similar to the studies of Mahoney (1996) and Hendricks (1996), they examined the simple historical simulation approach (full-valuation), as well as the equally weighted and exponentially weighted moving average parameter approaches (parametric). Despite the superior forecast performance of the parametric models, Jackson, Maude, and Perraudin found that the historical simulation method better represented the tail probabilities, especially at the 99% level of confidence, consistent with the results of Mahoney (1996) and Hendricks (1996). They noted larger sample windows may help alleviate the problem of large returns/losses occurring in the tails since longer time periods were better able to pick up extreme observations. However, consistent with Hendricks (1996), they found their parametric models to better explain time varying volatility and provide more accurate volatility forecasts. Overall, they concluded that the differences in forecasting performance were marginal between the class of estimators (parametric and non-parametric).

In contrast to the aforementioned studies that address the sensitivity and performance of VaR estimates to different estimating procedures, Marshall and Siegel (1997) examined how sensitive VaR estimates were across model builders (vendors) for the same estimation technique. They coined the potential variation among model builders using the same estimation technique as implementation risk. Similar to Jackson, Maude, and Perraudin (1997), Marshall and Siegel concluded that implementation risk may differ among asset classes examined, thus reinforcing the potential sensitivity of VaR models to a particular time series. In particular, they stated that "instrument classes with more complex structures generally produce greater variation in VaR estimates" (Marshall and Siegel, p.106). Among the various assets and vendors examined, they found the smallest level of implementation risks for foreign exchange (FX) forwards. They noted that for non-linear positions wide variation existed among the vendors for VaR estimates when using the RiskMetrics methodology. When using non-parametric (full-valuation) for FX options positions, they found a wide variation among the alternative non-parametric procedures used by vendors.

2.5 Implications from Literature Review

Clearly, the overwhelming emphasis in Value-at-Risk has come from the finance community, especially as it pertains to the need of firms to comply with regulatory requirements. Based on studies to date, there is little agreement as to the best procedure for developing the risk measure. However, initial evidence suggests that parametric methods provide accurate overall volatility estimates and accurate VaR estimates at lower levels of confidence (i.e., at the 99% level), but fail to represent time varying volatility. As suggested several times, the performance of VaR estimating techniques are likely to be sensitive to the data set used in developing estimates, the length of the forecast horizon, confidence level, and departures from assumed distributional forms (i.e.

normal). Other less quantifiable issues important to VaR are the ease of use, flexibility, cost of implementation, and degree to which management and investors find the risk measure useful. Literature related to VaR is continually growing as researchers attempt to reconcile several of the issues presented in this review.

2.6 The Potential Use of VAR in Agribusiness

Agriculture provides a unique laboratory to further explore VaR and to investigate many of the issues addressed in this paper. Several agricultural risk management problems have been examined in a multiproduct or portfolio context. In particular, the multiproduct hedging literature has used estimates of portfolio volatility in developing variances and correlations to develop multiproduct hedging ratios. Examples include the soybean crushing margin (Tzang and Leuthold 1990; Fackler and McNew 1993) and the cattle feeding margin (Peterson and Leuthold 1987). These situations provide realistic portfolios for examining the performance of alternative VaR estimation techniques under realistic portfolio conditions. To date, the performance of VaR techniques has not been rigorously tested on portfolios exposed to agricultural commodity price risk.

The use of agricultural prices would bring new data to the empirical evaluation of VaR. The performance of VaR techniques when applied to agricultural commodity prices might be quite different than those found with financial asset prices. Several of the proposed volatility forecasting methods suggested for developing VaR estimates, in particular GARCH, has been applied to agricultural prices (Aradhyudla and Holt 1998; Yang and Brorsen 1993). The exponentially weighted moving average technique advocated by J.P. Morgan's RiskMetrics may provide a useful alternative to multivariate GARCH procedures for developing time varying variance/covariance matrics for agricultural risk management purposes. The emphasis that VaR places on measuring tail behavior provides added motivation for testing common volatility estimation procedures and for their ability to forecast tail events in addition to overall volatility. Also, the fact that several agricultural product prices have associated futures and options contracts allow implied volatility estimates to be employed as VaR estimates. Researchers and practitioners have suggested the use of implied volatility estimates in developing VaR measures as being superior to other methods since implied volatility is the market's forecast of volatility. However, the performance of implied volatility in the context of VaR has not been rigorously examined. Furthermore, relevant risk horizons observed in agriculture tend to be longer than the daily horizon commonly used by financial practitioners in calculating VaR. This issue calls into question the performance of different volatility forecasting procedures to calculate VaR at horizons longer than one day.

Despite the obvious empirical applications, the use of VaR as a risk reporting and measurement tool has several practical applications for agricultural risk management. First and foremost, publicly traded agribusiness firms must comply with SEC regulations concerning the reporting of positions in highly market sensitive assets including spot commodity, futures, and options positions. At recent CFTC hearings regarding the lifting of the ban on agricultural trade options, VaR was proposed as a potential risk reporting measure to be used by firms to disclose their market risk exposure. Also, in the wake of the Hedge-to-Arrive crisis of 1996, the reporting of VaR may have been useful in adverting such a crises, a parallel to the justification of banking and securities regulators support for VaR and market risk disclosure. For example, VaR could have provided elevator manager and growers estimates of downside risk in accordance with positions held in Hedge-to-Arrive agreements. VaR also has potential use for agricultural lending institutions in the credit evaluation process. Agricultural lending institutions are indirectly exposed to various agricultural product price risks through the exposure of their borrowers.

The dynamic nature of agriculture as well as the proposed reduction of government programs creates a new risky environment in agriculture. Agribusinesses are exposed to multifaceted market risks. With the growing use and interest in VaR, there appears to be several practical applications for agriculture, as well as a greater need to assess and evaluate current methods of estimating volatility. The recent interest in VaR has created a new and additional motivation for accurate and meaningful measures of volatility and correlation. Despite the recent attention and popularity of VaR, this risk measure should only be viewed as another measure in the risk manager's toolkit and not a substitute for prudent risk management practices.

An agribusiness example of VaR can be constructed from a cattle feeding operation. A cattle feeder is exposed most notably to the variability in the output price of fed cattle and the input prices of feeder cattle and corn. The cattle feeder's profit margin is the difference between revenue generated from the sale of the fed cattle less the costs incurred from the purchase of feeder cattle and corn. For this dynamic operation, the feeder needs to observe the market volatility of the prices and calculate the VaR of the feeding margin to avoid excessive losses during any given period. This situation forms the focus of this paper.

Chapter Three

Data and Methodology

3. 1 Data Resources

In order to estimate VaR for the beef cattle feeding margin, a time-series return is necessary. Specifically, return series are constructed from Wednesday cash prices of fed cattle, feeder cattle, and corn. Wednesday is the day selected since trading volume is generally higher on Wednesdays and "weekend" effects are minimized for both cash and futures markets. These return series are defined as the following continuously compounded rate of return (percent change in price) defined as:

$$R_{t,i} = \ln(P_{t,i}) - \ln(P_{t-1,i}) \, , \qquad (3.1)$$

where $R_{t,i}$ is the weekly return of commodity i in period t, ln is the natural logarithm, and $P_{t,i}$ is the price at time t of commodity i (current Wednesday price). If a Wednesday price is not available, then a Tuesday price is used instead. The three weekly price series span from January, 1985 through December, 1999 providing 15 years (783 observations) of returns for estimation and out-of-sample testing.

Cash prices were provided by the Livestock Marketing Information Center. Fed cattle prices ($/cwt.) reflect the West Kansas market for 1100 to 1200 pound choice steers. Feeder cattle prices ($/cwt.) represent 600 to 700 pound feeder steers from west Kensas. No. 2 Yellow Corn prices ($/bu.) for Omaha, the closest market to the designed feedlots, account for the cost of feed.

Futures and options price data as well as interest rate data are also used in order to calculate implied volatilities, which will be incorporated in the variance/covariance method. The futures and options prices span from approximately 1989 till 1999. Both live cattle and feeder cattle futures and options are traded on the Chicago Mercantile Exchange. Live cattle futures and options are traded for the months of March, May, June, August, October and December, while feeder cattle futures and options are traded for the months of January, March, April, May, August, September, October and November. Corn futures and options are traded on the Chicago Board of Trade for the months of March, May, July, September, and December. A proxy for the risk free rate of interest is also needed when calculating implied volatilities. The interest rate used is the daily 3-month T-bill rate for the particular day that an implied volatility estimated is needed. The source for this interest rate data is the Federal Reserve Bank of Chicago (2000) website.

3.2 The Characteristics of Financial Data – Underlying Theoretical Foundation

3.2.1 Returns vs. Prices

In practice, the main reason for working with returns rather than prices is that returns have more attractive statistical properties than prices, as shown in Figure 3. Further, returns are often preferred to absolute price changes because the latter do not measure change in terms of a given price level, and the multiple-day gross return $1+R_t$ is given by the product of 1-day gross returns. Hence, the portfolio return is a weighted average of continuously compounded returns.

3.2.2 Distribution of Returns

Visual inspection of the data can be a useful way to help understand whether the assumptions of *iid* returns hold. Using the time-series of returns of the three price series in the model, we investigate whether the assumption of *iid*, is indeed valid. Figures 5, 6, and 7 show that the *iid* assumption is partially violated. That is these time series show clear evidence of volatility clustering. Periods of large returns are clustered and distinct from periods of small returns, which are also clustered. If we measure volatility in terms of variance, then the variance changes with time. Figures 8, 9, and 10 reflect clusters of large and small returns, which is clear evidence of heteroscedasticity or a non-constant of variance over time.

3.2.3 Correlation of the Clusters Between the Returns Series.

From Figures 8, 9, and 10, we can see that high volatility in feeder cattle returns generally coincide with high volatility in corn returns. Such correlation between the return of different series motivates the development of multivariate models, that is, models of returns that measure not only individual series variance (volatility), but also the correlation between return series.

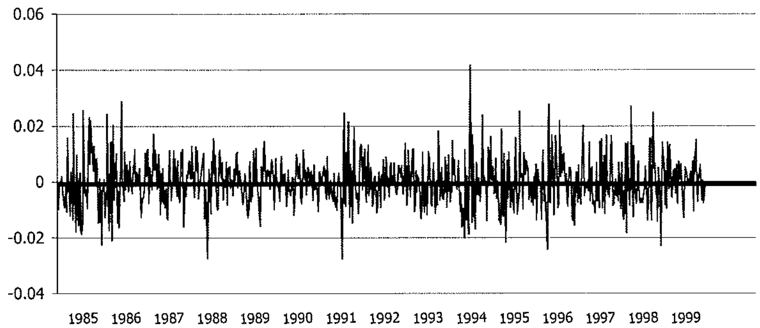

Figure 5. Return Series of Weekly Fed Cattle Prices

Source: Raw Data, Livestock Marketing Information Center

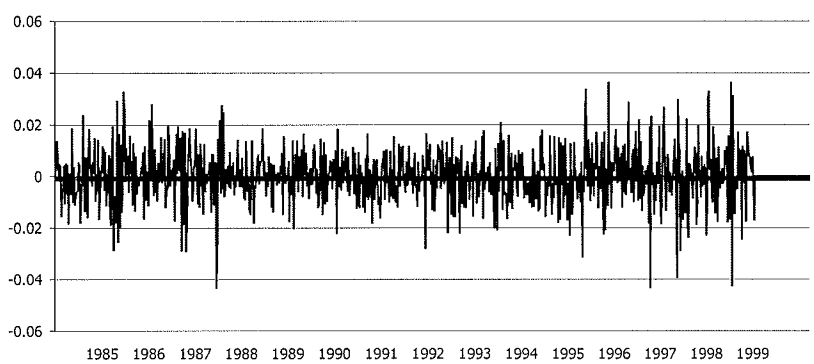

Figure 6. Return Series of Weekly Feeder Cattle Prices

Source: Raw Data, Livestock Marketing Information Center

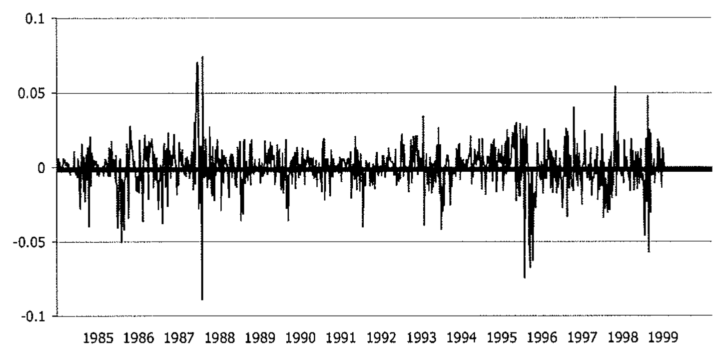

Figure 7. Return Series of Weekly Corn Prices

Source: Raw Data, Livestock Marketing Information Center

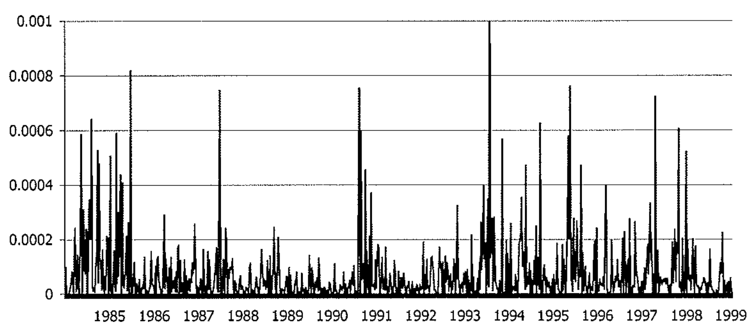

Figure 8. Squared Returns of Fed Cattle

Source: Raw Data, Livestock Marketing Information Center

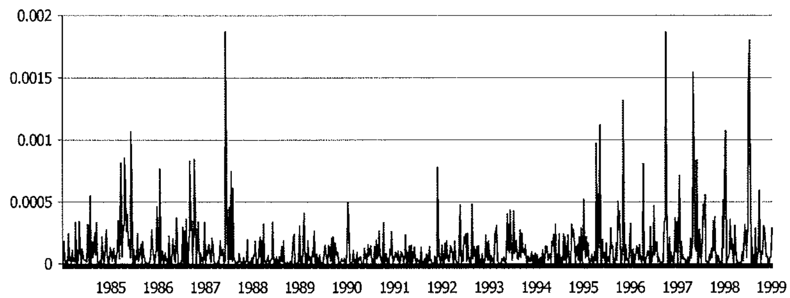

Figure 9. Squared Returns of Feeder Cattle

Source: Raw Data, Livestock Marketing Information Center

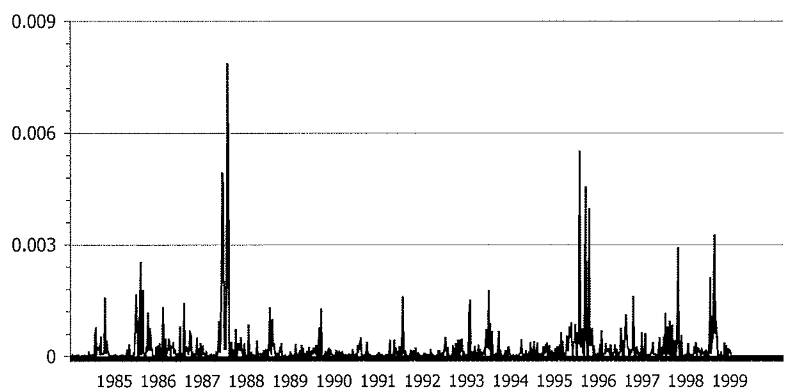

Figure 10. Squared Returns of Corn

Source: Raw Data, Livestock Marketing Information Center

3.2.4 Autocorrelation

In Figures 8, 9, and 10, the persistence displayed by the volatility clusters shows some evidence of autocorrelation. That is, the variances of the series are correlated across time. If returns are statistically independent over time, then they are not autocorrelated. Therefore, a natural method for determining if returns are statistically independent is to test whether or not they are autocorrelated. An often cited method is the Box-Ljung (BL) test statistic, defined as

$$BL(p) = T^*(T+2)\sum_{k=1}^{P}\sigma_k^2 \qquad (3.2)$$

Under the null hypothesis that a time series is not autocorrelated, BL (p) is distributed chi-squared with p degrees of freedom. p denotes the number of autocorrelations used to estimate the statistic. We applied this test to the weekly feeder cattle returns, using p=10 which has an implied critical value of 18.31 at a 95% confidence level. The preceding test shows little evidence of autocorrelation for weekly returns. But when we applied the BL test to squared weekly return, we found autocorrelation.

3.3 Methodology

In defining the cattle feeding margin, Leuthold and Mokler (1979), Peterson and Leuthold (1987), and Schroeder and Hayenga (1988) describe similar cattle feeding scenarios that incorporate fixed feeding technology. It is assumed that cattle are placed on feed at 650 pounds and fed to 1100 pounds, consuming 45 bushels of corn in the process.

Based on this technology, the cattle feeding margin is defined as (ignoring any fixed costs):

Gross Margin $_t$ (\$/head)= (fed cattle price $_t$, \$/cwt.) 11 - (feeder cattle price $_t$, \$/cwt.) 6.5 – (corn price $_t$, \$/bu.) 45 (3.3)

For most middle to large size feedlots, cattle are continually marketed and placed on feed. As well, feedlots with a capacity of 30,000 head or more typically do not maintain corn inventories for extended periods. Therefore, it is assumed that cattle feeding is a continuous process with decision makers routinely evaluating the variability of fed cattle, feeder cattle and corn prices in a portfolio framework. Because of this, VaR measures are estimated and evaluated for weekly horizons consistent with the periodicity of the three price return series.

The portfolio risk, measured by the variance of the cattle feeding margin can thus be expressed as:

$$\sigma_p^2 = (11p_{fc})^2\sigma_{fc}^2 + (6.5P_{fd})^2\sigma_{fd}^2 + (45P_c)^2\sigma_c^2 + 2*(11p_{fc})(6.5P_{fd})\rho_{fc,fd}\sigma_{fc}\sigma_{fd} + 2*(11p_{fc})(45P_c)\rho_{fc,c}\sigma_{fc}\sigma_c + 2(6.5P_{fd})(45P_c)\rho_{fd,c}\sigma_{fd}\sigma_c \tag{3.4}$$

where $\sigma_{fc}^2, \sigma_{fd}^2, \sigma_c^2$ are the variance of fed cattle, feeder cattle, and corn returns respectively, $\rho_{fc,fd}, \rho_{fc,c}, \rho_{fd,c}$ are the respective correlation coefficients between returns. Portfolio weights are defined as $P_{i,}Q_i$ where P_i is the price of commodity i and Q_i is the quantity of commodity i based on the assumed production technology (11 for fed cattle, 6.5 for feeder cattle and 45 for corn) to make it expressed in dollar terms. Considering

Equation 3.4 in a forecasting framework such that the individual variances (volatility) and correlation coefficients are forecasts, VaR for any given week t is

$$\mathrm{VaR}_{p,t} = \alpha\sigma_{p,t+1} \tag{3.5}$$

where $\sigma_{p,t+1}$ is the portfolio volatility forecast of the cattle feeding margin ($/head) and α is the scaling factor corresponding to the desired confidence level. Several forecasting procedures are employed to estimate the individual volatilities and correlation used in Equation 3.4, all of which have been advocated for use in developing VaR measures and/or used in previous empirical studies related to VaR. These methods include a long-run historical average, a 310-week historical moving average, GARCH(1,1), exponentially weighted moving averages advocated by J.P .Morgan's RiskMetrics, and implied volatilities from options on futures contracts.

For all forecasting approaches, the initial data used for the estimation of the models' parameters are drawn from the period 1985 to 1990 (Week T=1,2,....310). Thus, the first week for which out-of-sample forecasts are obtained is Jan 1991(T=311). As the sample period covers 783 weeks, out-of-sample forecasts are constructed for weeks 311 to 783, totalling 473 forecasts.

3.3.1 Historical Averages

For both long-run and the 310-week moving average, the volatility forecast is defined as:

$$\sigma_{i,t+1} = \sqrt{\frac{1}{T}\sum_{m=0}^{T-1} R_{i,t-m}^{2}} \tag{3.6}$$

where $\sigma_{i,t+1}$ is the volatility forecast for commodity i, T is the number of past squared returns used in developing the forecast, and $R_{i,t}^{2}$ is the realized squared return for commodity i in week t where the mean return of the series is constrained to zero. At each week that a forecast is made, this method uses all the data available up to that point. Similarly, covariance forecasts between the three commodity price series, take the following form:

$$\sigma_{ij,t+1} = \frac{1}{T}\sum_{m=0}^{T-1} R_{i,t-m,} R_{j,t-m} \tag{3.7}$$

where $\sigma_{ij,t+1}$ is the forecasted covariance between commodity i and commodity j and $R_{i,t}$ and $R_{j,t}$ are returns for commodity i and j respectively. In the case of the long-run historical average, the sample size is anchored to the first return observation (growing sample size). For the 310-week historical moving average, T is equal to 310, dropping old observations at each time period T. Moving averages (or moving windows) are very similar to long-run historical averages but are thought to be more sensitive to structural change and observed time variation than models that use a growing sample size.

3.3.2 GARCH

Models of conditional volatility, in particular GARCH (Generalized Autoregressive Conditional Heteroskedasticity), have dominated the volatility forecasting literature. The GARCH (1,1) specification has received considerable attention and has often been found to be the best specification for conditional volatility among alternative and often more complex variants of GARCH. However, controversy exists as to whether any GARCH specification provides superior volatility forecasts to simpler time-series alternatives, especially in light of the difficulty in estimating GARCH models.

The tri-variate GARCH model involves the estimation of conditional mean and variance equations, which employed,

$$R_t = \alpha_t \varepsilon_t \qquad (3.8)$$

where $\varepsilon_t \sim$ N(0,1) and

$$\sigma_{t,i}^2 = \alpha_0 + \alpha_1 R_{t-1,i}{}^2 + \alpha_2 \sigma_{t-1,i}^2 \qquad (3.9)$$

where $\sigma_{t,i}^2$ is the conditional variance at time t of commodity i, $\sigma_{t-1,i}^2$ is the variance in the previous period of commodity i, $R_{t-1,i}^2$ is the squared return in the previous period where the mean return is set to zero and $\alpha_0, \alpha_1, \alpha_2$ are the Maximum Likelihood GARCH estimates (MLE). MLE of the GARCH model is carried out by using a variant of the Berndt et al. (1974) optimization algorithm that constrains parameter estimates in the variance equations to be nonnegative. Similar to historical averages, a growing sample size is used in estimating GARCH. Therefore, each week that a forecast is made, all data up to that point are used. This is done in order to produce meaningful GARCH forecasts that conform to the constraints that α_1 and α_2 are non-negative and that α_1 + α_2 <1 ensure long-run stability of the model.

3.3.3 RiskMetrics (Exponentially Weighted Moving Average)

In response to the need for simplistic metrics for developing VaR measures, JP Morgan, through their RiskMetrics documentation, advocates the use of an exponentially weighted moving average model of asset return volatility incorporating a fixed decay factor λ, (0<λ<1). This parameter determines the relative weights that are applied to the observations (returns) and the effective amount of data used in estimating volatility. This model, also known as the RiskMetrics method, is touted for its ease of estimation and its ability to represent time-varying volatility without resorting to GARCH estimation. Because of this, the J.P. Morgan's risk methodology for estimation volatilities and covariances (correlations) has been a major impetus for the use of VaR estimations. The RiskMetrics volatility forecast is:

$$\sigma_{i,t+1} = \sqrt{\lambda \sigma_{i,t}^{2} + (1-\lambda) R_{i,t}^{2}} \qquad (3.10)$$

where λ is the pre-determined decay factor and $\sigma_{i,t}^{2}$ is the t-period variance forecast. Time varying covariances are forecasted in a similar fashion such that:

$$\sigma_{ij,t+1} = \lambda \sigma_{ij,t} + (1-\lambda) R_{i,t} R_{j,t} \qquad (3.11)$$

Three fixed decay factors are used, including λ=0.94 and λ=0.97, which are recommended by RiskMetrics for weekly and monthly data, respectively, as well as a λ optimized for weekly data over the respective sample period of the three return series via MLE techniques (λ=0.96).

This approach captures the dynamic features of volatility by giving the latest observations the most weight in the estimation. This has two important advantages. First, volatility reacts faster to shocks in the market as recent data carry more weight than data in the distant past. Second, following a shock (a large return), volatility declines exponentially as the weight of the shock observation falls. In contrast, the historical moving average estimate only has the effect of a relatively abrupt change in the standard deviation once the shock falls out of the measurement sample.

3.3.4 Implied Volatilities

It is a widely held notion, especially among academics, that implied volatility forecasts derived from option premia are superior to any alternative volatility forecast since it is in essence the markets' forecast of volatility. Despite this belief, enough evidence exists to fuel a controversy over the predictive accuracy of implied volatility forecasts to those of time series specifications. Because of this, implied volatilities are also used in this study and their forecasting ability is evaluated relative to other forecasts of return volatility.

Several theoretical issues exist regarding the estimation of implied volatility (e.g. potential violation of pricing model assumptions) which are beyond the scope of this paper. Hence this research takes a risk management perspective where practicality in estimating implied volatilities is emphasized. First, in the absence of exchange traded options contracts written specifically on cash price, it is assumed that volatilities implied from options written on live cattle, feeder cattle, and corn futures provide a reasonable proxy for the option market's assessment of future price volatility of cash prices. Second, the option pricing model used to derive implied volatilities is the popular Black-1976 model for options on futures contracts. Since the options on futures contracts are of the American type, the use of a European pricing model for eliciting implied volatilities can introduce a small upward bias in the volatility estimate due to the early exercise premium of American options. However, this bias has been found to be small for short-term options that are at-the money. Furthermore, studies examining alternative estimation procedures (weighting schemes) for implied volatility, (e.g., calculating implied volatility as the average implied volatility across various strike prices), have found that implied volatilities taken from the nearest at-the-money options provide the most accurate volatility estimates. At-or near-the-money options tend to contain the most information regarding volatility because they are usually the most traded options (highest volume) and subsequently yield the largest vega. As well, Jorion (1997) also notes that the averaging of implied volatilities from both puts and calls helps to reduce measurement error.

Therefore, in accordance with these observations, the implied volatilities used for this study are computed as the simple average of the implied volatility derived from nearby, at-the-money (or closest to at-the-money), put and call options. The framework used in this study is based on the model developed by Hull and White (1997). Given the availability of market prices for options, the HW model provides an expression of the variance that can be used to estimate the expectation. Because the variance of the underlying asset is the only unknown argument in the Black-1976 formula, the implied variance is the value of this argument that equates the market price to the theoretical Black-1976 price. Since the Black-1976 formula is essentially a linear function of the standard deviation for at-the-money options, $E[BS(V)|I_t]$ approximately equals $BS[E(v)|I_t]$. For this reason, we use a sample of at-the-money options and therefore interpret the implied variance as the market's assessment of return of value over the remaining life of the option. Since implied volatilities yield annualized estimates, it is necessary to convert these annualized estimates to weekly estimates such that:

$$IV_{i,t+1} = \frac{IV_{(annual),i,t}}{\sqrt{52}} \qquad (3.12)$$

where $IV_{i,t+1}$ is the volatility forecast for commodity i at week t+1,and $IV_{(annual),i,t}$ is the annualized implied volatility estimate.

Utilizing the above procedure for forecasting volatilities and covariances, correlation forecasts used in Equation 3.7 are computed as:

$$\rho_{ij,t+1} = \frac{\sigma_{ij,t+1}}{\sigma_{i,t+1}\sigma_{j,t+1}} \qquad (3.13)$$

where $\sigma_{i,t+1}$ and $\sigma_{j,t+1}$ are the volatility forecasts for commodities i and j and $\sigma_{ij,t+1}$ is the forecasted covariance between commodities i and j. It is important to note that both the GARCH (1,1) and the implied volatilities, Equations 3.9 and 3.12 respectively, do not have corresponding methods to explicitly develop covariances needed for developing correlation forecasts in Equation 3.7. Because of this, the portfolio variance (volatility) forecast in Equation 3.7 is created using either GARCH (1,1) or implied volatilities with correlations estimated from the long-run historical average, 310-week moving average, and J.P. Morgan's RiskMetrics methods respectively. These are referred to as "mixed" VaR models throughout this paper.

Since the use of RiskMetrics volatilities and correlations is advocated as a simple alternative to multivariate GARCH procedures, a constant correlation MGARCH procedure is also used. Specifically the constant correlation MGARCH model presented by Bollerslev, Chou, and Kroner (1990) assumes that conditional correlations between commodity price returns are constant over time and that individual commodity price return variances follow a univariate GARCH(1,1) process. Thus the model can be shown as:

$$\sigma^2_{ii,t+1} = c_{ii} + \alpha_{ii} R^2_{ii,t} + \beta_{ii} \sigma^2_{ii,t} \qquad (3.14)$$

$$\sigma_{ij,t+1} = \rho_{ij,t+1} \sigma_{ii,t+1} \sigma_{jj,t+1} \qquad (3.15)$$

where $\sigma^2_{ii,t+1}$ is the conditional variance of asset i for t+1, $\sigma_{ij,t+1}$ is the conditional covariance, $\rho_{ij,t+1}$ is the constant correlation forecast between assets i and j, and $\sigma_{ii,t+1}$ is the conditional standard deviation of asset i at t+1. In all cases, i≠j, this model provides a positive definite covariance matrix if all parameters are positive, $\alpha_{ii} + \beta_{ii} < 1$ and $\rho_{ij,t+1}$ is between –1 and 1. The MGARCH estimate is then compared to the more simplistic procedures where volatilities and covariances (correlations) are estimated independent of each other.

Thus using the described variance-covariance methods, weekly VaR measures are estimated from Jan 1991 through Sept 1999 providing 473 weekly forecasts of volatility and correlations among the three return series. VaR estimates are calculated for the 90%

(α=1.28), 95% (α=1.65) and 99% (α=2.33) levels of confidence. Each of the VaR measures developed and tested is outlined in Table 1.

In addition to the above mentioned VaR estimates, a simple historical simulation (introduced in Chapter Two) is also developed for the 90%, 95% and 99% confidence levels. Historical simulation models require the entire return distribution with the VaR designated as the quantile associated with the desired level of confidence. The historical simulation procedure used follows the methods of Linsmeier and Pearson (1996). First, at time period t, the cattle feeding margin is calculated as in Equation 3.4. Second, the prices of fed cattle, feeder cattle and corn observed at time t are exposed to their respective previous 310 weekly returns such that $P^*_t = P_t(1+R_{t-T})$ for all T=1….310. Third, the cattle feeding margin is recalculated using these new prices (P*), creating 310 new values of the cattle feeding margin. These margins are then subtracted from the actual feeding margins realized at week t, yielding 310 differences between the actual cattle feeding margins and the simulated values of the feeding margin previously generated. Finally, from the distribution of these differences, the quantile associated with a desired confidence level (e.g., 5% for the 95% level of confidence) becomes the VaR estimate.

Table 1 Value-at-Risk Measures Index

Abbreviations	Description
HIS-310	310-day moving average volatilities and correlations
HIS-MOV	Long-run historical average volatilities and correlations
GARCH (1, 1)	Multivariate GARCH
RMOPT	Risk Metrics volatilities and correlations with the optimal λ
RM97	Risk Metrics volatilities and correlations with $\lambda=0.97$
RM94	Risk Metrics volatilities and correlations with $\lambda=0.94$
IVRM97	Implied volatilities and RM97 correlations
IVH310	Implied volatilities and HIS310 correlations
IVHISMOV	Implied volatilities and HIS-MOV correlations
HISSIM	Historical simulations
COMP	Simple average composite of RM97 and HISSIM

Chapter Four

Evaluation and Empirical Results

4.1 Evaluation

The specific parametric and historical simulation VaR estimates in Table 2 through Table 4 are evaluated on their ability to predict large losses (decreases) in the cattle feeding margin resulting from fluctuations in fed cattle, feeder cattle, and corn prices. If actual portfolio losses over the desired horizon (one week) exceed the VaR estimate, a violation occurs. Hence, if violations are in excess to that implied by a particular confidence level, the VaR measure is considered inadequate for measuring large losses of the cattle feeding margin. To determine if violations are commensurate with the designated confidence level of VaR, a likelihood ratio test is developed following the procedures of Lopez (1995 and 1997). The null hypothesis is $\omega = \omega*$ where ω is the desired coverage level (e.g., 5%) corresponding to the given confidence level (e.g., 95%), ω is X/N where X is the number of realized violations and N is the number of out-of-sample observations.

$$\Pr(\mathrm{X}\,;\,\varpi, \mathrm{N}) = \binom{N}{X}\omega^{X}(1-\omega)^{N-X} \qquad (4.1)$$

and the likelihood ratio test statistic is

$$\mathrm{LR}\,(\omega) = 2\;\{\;\ln[\omega*^{X}\,(1-\omega*)^{N-X}] - \ln[\omega^{X}\,(1-\omega)^{N-X}]\,\} \qquad (4.2)$$

which has an asymptotic χ^2 distribution with 1 degree of freedom. Note that the LR test of this null hypothesis is uniformly most powerful for a given N. However, the finite

Table 2 Evaluation of VaR Measures for the 90% Confidence Level

VaR Measure	Number of Violation (N=473)	Percent Violations	Average Size Violation	Maximum Violation	Minimum Violation	LR Statistic	Z Statistic	Average VaR Estimate
HIS-310	52	14.16	$7.96	$32.17	$0.02	0.52	0.72	$22.11
HIS-MOV	69	14.59	$8.78	$32.83	$0.67	4.79	2.19	$21.45
GARCH(1,1)	73	15.43	$8.06	$35.44	$0.45	5.11	2.34	$20.96
RMOPT	50	11.84	$8.45	$29.09	$0.28	0.13	0.41	$22.06
RM97	53	11.42	$7.03	$27.74	$0.26	0.77	0.87	$22.13
RM94	51	11.42	$8.32	$27.99	$0.05	0.25	0.57	$22.11
IVRM97	59	16.07	$9.66	$33.14	$0.94	2.95	1.79	$19.96
IVH150	71	16.28	$9.87	$35.23	$0.88	8.43	3.63	$19.08
IVHISMOV	72	15.22	$11.04	$39.46	$0.75	12.56	3.82	$18.66
HISSIM	59	14.59	$7.54	$28.71	$0.06	2.95	1.79	$22.14
COMP	51	10.57	$5.46	$29.05	$0.14	0.25	0.57	$21.52

Notes :

1. N is the number of weekly VaR estimates in portfolio value.
2. The Chi-Squared critical value with 5% confidence level is 3.841.
3. The critical Z value with 5% confidence level is 1.96.

Table 3 Evaluation of VaR Measures for the 95% Confidence Level

VaR Measure	Number of Violation (N=473)	Percent Violations	Average Size Violation	Maximum Violation	Minimum Violation	LR Statistic	Z Statistic	Average VaR Estimate
HIS-31 0	27	7.41	$7.14	$30.26	$0.67	2.01	1.13	$28.74
HIS-MOV	34	7.93	$8.15	$28.76	$0.45	3.96	2.18	$26.89
GARCH(1,1)	42	8.96	$7.13	$29.08	$0.36	7.99	3.41	$26.04
RMOPT	26	5.60	$7.68	$26.54	$0.64	0.31	0.50	$28.47
RM97	27	6.15	$6.56	$25.13	$0.02	0.49	0.71	$28.26
RM94	27	6.15	$7.64	$25.67	$0.34	0.49	0.71	$28.25
IVRM97	39	8.45	$8.41	$31.74	$0.86	8.07	3.24	$25.43
IVH150	40	8.77	$8.85	$33.87	$0.76	9.00	3.45	$24.55
IVHISMOV	48	10.11	$9.06	$36.98	$0.88	18.77	5.14	$23.98
HISSIM	30	8.17	$6.71	$26.73	$0.22	2.14	1.34	$28.04
COMP	29	7.14	$6.45	$27.71	$0.26	1.19	1.13	$28.26

Notes:

1. N is the number of weekly VaR estimates in portfolio value.
2. The Chi-Squared critical value with 5% confidence level is 3.841.
3. The critical Z value with 5% confidence level is 1.96.

Table 4 Evaluation of VaR Measures for the 99% Confidence Level

VaR Measure	Number of Violation (N=473)	Percent Violations	Average Size Violation	Maximum Violation	Minimum Violation	LR Statistic	Z Statistic	Average VaR Estimate
HIS-310	5	1.48	$5.97	$15.11	$0.68	0.03	0.12	$40.77
HIS-MOV	9	2.33	$6.02	$16.31	$0.76	2.79	1.97	$40.13
GARCH(1,1)	15	3.17	$5.84	$19.66	$1.32	8.77	3.99	$37.41
RMOPT	9	2.33	$5.09	$14.75	$0.47	2.83	1.97	$41.06
RM97	5	1.48	$5.71	$14.32	$0.68	0.03	0.12	$39.87
RM94	10	2.57	$5.43	$15.28	$0.37	4.13	2.44	$39.92
IVRM97	15	3.81	$4.56	$22.47	$0.56	13.11	4.75	$35.56
IVH150	16	4.02	$4.87	$23.89	$0.78	15.87	5.21	$35.44
IVHISMOV	25	5.71	$5.96	$27.98	$0.89	37.88	9.37	$32.11
HISSIM	9	2.33	$5.41	$18.07	$0.25	2.88	1.97	$38.09
COMP	5	1.48	$6.01	$17.97	$1.65	0.02	0.12	$39.06

Notes:

1. N is the number of weekly VaR estimates in portfolio value.
2. The Chi-Squared critical value with 5% confidence level is 3.841.
3. The critical Z value with 5% confidence level is 1.96.

sample size and power characteristics of this test are of interest here. With respect to size, the finite sample distribution for a specific (ω, N) pair may be sufficiently different from the χ^2 distribution that the asymptotic critical values may be inappropriate. The finite-sample distribution for a specific (ω, N) pair can be determined via simulation and compared to the asymptotic one in order to establish the actual size of the test. As for power, Kupiec (1995) describes how this test has a limited ability to distinguish among alternative hypotheses and thus low power, even in moderately large samples.

Similarly, a test of bias in VaR estimates is conducted consistent with the procedures of Mahoney (1996, pp. 206-207), that is based on a binomial probability distribution. The expectation of the number of violations of VaR estimates is N(1-c) where N is the number of out-of-sample observations and c is the confidence level expressed in decimal form (e.g., 0.95 for 95% level of confidence). The variance of this estimate is Nc(1-c). Thus, the test for bias is defined as a Z test, which in large samples is distributed normally, such that:

$$Z = \frac{L_{realized} - N(1-c)}{\sqrt{Nc(1-c)}} \qquad (4.3)$$

Where $L_{realized}$ equals the number of observed violations of VaR at a given confidence level c (Mahoney 1996). Hence, if the Z statistic is significantly positive (negative), then VaR regularly underestimates (overestimates) actual downside risks.

Summary statistics of the VaR violations are also used to evaluate the VaR models including the number of violations realized (X), the percentage of violations that occurred over the sample period (X/N)*100, the average size violation ("sum values of violations"

/X), the maximum violation and the minimum violation. Therefore, if several VaR measures are determined to be "well calibrated"(e.g., $\omega = \omega^*$) the preferred VaR model among alternatives is the one with the smallest of these summary statistics.

4.2 Empirical Results

Over the sample period from Jan 1985 to Dec 1999, the average feeding margin as defined in Equation 3.3 is $137.74 per head. The largest feeding margin over this time period is $ 270.87 per head, realized in week of 11/01/96, while the smallest feeding margin is $15.68 in week 08/16/91. The largest single weekly loss (decrease) in the cattle feeding margin (portfolio) over the sample period, -$34.79, occurred from 07/26/91 to 08/02/91. For all of the VaR measures tested in table 1, this large change resulted in the largest (maximum) violation of VaR for all confidence levels tested; a rare event since losses like these are expected to occur less than 1% of the time. Using this event to illustrate a violation of VaR, the VaR estimate on 07/26/91 is $20.47 with 99% confidence level. Based on this VaR estimate, it is predicted that the cattle feeding margin would not decrease from its current level of $76.65 by more than $20.47 with 99% confidence. However, over the next week, the cattle feeding margin decreases by $34.79 to $41.86, a violation of the VaR estimate by the size of $14.32.

The results of the likelihood ratio test, Z test, and summary statistics of the VaR violations are presented in tables 2 through table 4. Based on the results of the likelihood ratio and Z tests (Equations 4.2 and 4.3), the RiskMetrics models (RM97, RM94, and RMOPT), the historical moving average model (HIS-310), and the full valuation historical simulation (HISSIM) provide coverage consistent with all three confidence levels (90%, 95%, and 99%). In other words, in each case, these VaR specifications fail to reject the null hypothesis that the number of violations realized over the sample period equals the number implied by the predetermined confidence level ($\omega = \omega^*$). All of the other VaR models, except IVRM97 at the 90% level have more violations occurring than accepted by the predetermined confidence level. For those VaR measures that have more violations than allowed, the associated Z statistic is both positive and significant suggesting that those specifications produce estimates that consistently underestimate the true downside risk of the cattle feeding margin.

Examining each of the confidence levels individually, at the 90% confidence level (see table 2), several VaR measures fail to reject the null hypothesis of $\omega = \omega^*$, including HIS310, RMOPT, RM94, RM97, HISSIM and IVRM97. Of these, RMOPT has the smallest values of both the likelihood ratio and Z statistics while IVRM97 and HISSIM have the largest. However, RM97 has the smallest average size violation, maximum violation, and minimum violation at \$7.03, \$28.47, and \$0.26 respectively. Of the well-calibrated VaR measures at the 95% confidence level (table 3), again RMOPT has the smallest values of the test statistics and percent violation (5.6 %) that are closest to what would be expected by the predetermined confidence level of 95%. Both RM97 and RM94 are next with likelihood ratio statistics and Z statistics at 0.49 and 0.71 respectively. Again in this case, RM97 has the smaller average size violation, maximum violation, and minimum violation with the average size violation being approximately \$1.12 per head smaller than that for RMOPT (\$6.56 vs. \$7.68) and \$1.08 per head smaller than RM94 ($6.56 vs. $7.64). It is difficult to judge whether these differences in the size of VaR violations on average over the sample period are economically significant. Interestingly, at the 99% level of confidence, where violations of VaR are expected to occur no greater than 1% of the time (Table 4), both RM97 and HIS-310 have the same values of likelihood ratio and Z statistics at 0.03 and 0.12 respectively. As with the 90% and 95% confidence level, RM97 again has the smallest maximum violation.

Since it is well known that composite forecasting techniques often yield superior forecasts, a composite VaR estimate is also created and examined versus the individual models. Based on the findings discussed above, the composite measure is constructed as a simple average of RM97 and HISSIM (COMP). These two VaR measures were chosen to be combined since they are both constructed using different methods (parametric vs. full valuation). COMP is found to provide coverage consistent with all three confidence levels and provides improvement over HISSIM at all confidence levels based on the percentage of violations realized and subsequently the values of the test statistics. In fact at the 90% level, COMP provided improvement over both of its component forecasts (RM97 and HISTSIM) based on the size of the LR and Z statistics.

The results presented in tables 2 through table 4 also suggest that performance of any VAR measure is greatly affected by the correlation structure incorporated. Those VaR models that combine univariate volatilities in conjunction with alternative correlation estimates (mixed models) consistently underestimate the true downside risk of the cattle feeding margin. This is evident since the Z statistics for these models are positive and significant and the average VaR estimates are smaller than those of the best performing models (e.g., RM97). However, performance of the mixed VaR models improves as the correlations more from being long-run historical to conditional RiskMetrics (e.g., IVHISMOV to IVRM97). The parametric VaR measures found to be well calibrated across confidence levels use volatilities and correlations that are estimated from the same underlying method (i.e., RiskMetrics). This observation calls into question the computational validity of using implied volatility or another univariate volatility estimation procedure for VaR that doesn't have a corresponding way of defining covariances and subsequently correlations. Furthermore, the weak performance of both multivariate GARCH specifications is likely due to the constant correlation assumption incorporated which was necessary to provide a positive definite covariance matrix as well as model convergence.

Interestingly, the majority of violations occurred during the period from April to October, using RM97 at the 90% level of confidence, 41 out of 62 violations (66% of violations) occur from April to October. During this time, 12 out of 62 violations (20%) occur in June while 27 violations (43%) occur from June through August. Similarly, at a 95% level of confidence, the April through October time periods saw 22 out of the 32 violations while 8 out of 22 (25%) are realized during the month of June alone. In addition, at the 99% confidence level, 5 out of the 6 violations were realized during the May to October time span. These observations are consistent with known increased price variability of fed cattle and corn prices during these months.

A good illustration to show that RM97 is superior to the other one, say IVRM97, is to trace the previous example we show in chapter two on the application of VaR in loan decisions. What is the difference of calculating VaR by using these two methods and how will the decision be affected by this? The gross feeding margin calculated on July 2 is $93.25, while VaR estimate for Dec 31,1999, six months later, is $85.52 with 5% confidence level, which means that the cattle feeding would not decrease from the current level of $93.25 by more than $85.52. By adopting IVRM97 method, VaR estimate for Dec 31,1999 is $66.97 with 5% confidence level. Based on an expected gross margin $75 (per head), by taking this loan, a decision would be made to accept a loan for this amount under the calculation of IVRM97 ($66.97), while with the result of $85.52 from RM97, the loan would not be made. Since IVRM97 is not as robust in our research from historical data, it may underestimate the risk of a management decision and potentially bring great losses to the business. VaR can also be used to compared with other investment alternatives to decide which one is the best one (the less riskier one) to invest to obtain an expected rate of return.

Chapter Five

Summary and Conclusions

This research assessed the performance of alternative methods to forecast VaR in cattle feeding operations. The methods recommended by J.P. Morgan's RiskMetrics, in particular using λ= 0.97, provide an accurate and robust specification for a covariance matrix in calculating weekly parametric VaR for the examined portfolio (the cattle feeding margin). However, other specifications, such as the other RiskMetrics specifications as well as the simple historical simulation (full-valuation procedure), also produce well-calibrated VaR measures for all three confidence levels examined. Therefore, the conclusion as to the superiority of the RiskMetrics method using λ=0.97 is made with caution. Overall, among the well-calibrated VaR measures, it is difficult to deem one measure to be the best. Any improvement provided by the RM97 relative to the other well-calibrated VaR models is fairly minimal and most likely not economically significant. Furthermore, evaluation based on the summary statistics presented, beyond the results of the LR test and Z test, is somewhat subjective. However, RM97 does have the smallest maximum violation among all VaR models for each of the three confidence levels examined. Hence, for the largest violation that occurs from 07/26/91 to 08/02/91, RM97 has the most conservative VaR estimate among all tested.

The fact that both parametric procedures (e.g. RiskMetrics) and full-valuation (e.g., historical simulation) are found to provide well-calibrated VaR measures is most likely due to the fact that the cattle feeding margin, as defined in this study, is a portfolio of linear instruments (cash prices). It is concluded that at least for this portfolio, correlations are more important to the overall performance of a particular VaR measure than volatilities. Furthermore, the majority of violations of VaR occur during time of observed seasonal increases in the volatility of fed cattle and corn returns. Because of this, risk managers that build VaR models in which the portfolio of interest contains positions in agricultural commodities or other seasonal commodities should be more cautious of their VaR estimates during these known times of seasonal volatility.

This study is the first attempt at empirically examining the performance of various VaR measures in the context of an agricultural enterprise portfolio (e.g., cattle feeding). To date, all known empirical studies examining the performance of alternative VaR measures have been conducted in the context of portfolios containing currency, interest rate, or equity data with portfolios often developed randomly (Mahoney 1996; Hendricks 1996). The cattle feeding margin provides a realistic alternative portfolio, as well as new data, for studying existing techniques of VaR estimation. Although most research in risk management deals with optimal hedging strategies and ratios, the lack of a transparent disclosure and reporting system can also cause great losses for an agribusiness entity. It is demanding to set up a complete system to combine VaR and hedging strategies together for weekly or monthly risk detection and portfolio adjustment. Because VaR is an intuitive and simplistic method, it can provide a warning sign to management once the risk value exceeds their limit. The process used to calculate VaR can help to decide where to possibly trim risk exposure. For the investor, the VaR reporting system can inform them of the potential risks that are associated with an expected rate of return. Also, with the popularity of adopting crop revenue or yield insurance, VaR can be used to evaluate the cost associated with this insurance.

The results of this study also provide an impetus for further research in the area of VaR. For instance, research is needed that focuses on the applicability and performance of VaR in the context of other agricultural prices and portfolios as well as the performance of alternative parametric and full-valuation procedures when options positions, which have a non-linear payoff structure, are included in a portfolio. Therefore, as interest and use of VaR increases among risk managers, research should focus on models that are robust for a variety of prices and portfolios.

Appendix One

Summary of Estimation Methods

1. Gross Margin ($/head): based on the fixed feeding technology and ignoring any fixed costs

Gross Margin $_t$ ($/head)= (fed cattle price $_t$, $/cwt.) 11 - (feeder cattle price $_t$, $/cwt.) 6.5 – (corn price $_t$, $/bu.) 45

2. Portfolio Risk: measured by the variance cattle feeding margin

$$\sigma_p^2 = (11p_{fc})^2\sigma_{fc}^2 + (6.5P_{fd})^2\sigma_{fd}^2 + (45P_c)^2\sigma_c^2 + 2*(11p_{fc})(6.5P_{fd})\rho_{fc,fd}\sigma_{fc}\sigma_{fd} + 2*(11p_{fc})(45P_c)\rho_{fc,c}\sigma_{fc}\sigma_c + 2(6.5P_{fd})(45P_c)\rho_{fd,c}\sigma_{fd}\sigma_c$$

3. HIS-310: 310-day moving average volatilities and correlations (the sample size is fixed at 310)

Volatilities Forecast: $\sigma_{i,t+1} = \sqrt{\frac{1}{T}\sum_{m=0}^{T-1} R_{i,t-m}^2}$ (T=310)

Correlations Forecast: $\sigma_{ij,t+1} = \frac{1}{T}\sum_{m=0}^{T-1} R_{i,t-m,}R_{j,t-m}$ (T=310)

4. HIS-MOV: Long-run historical average volatilities and correlations

Volatilities Forecast: $\sigma_{i,t+1} = \sqrt{\frac{1}{T}\sum_{m=0}^{T-1} R_{i,t-m}^2}$ (T=310,…,784)

Correlations Forecast: $\sigma_{ij,t+1} = \frac{1}{T}\sum_{m=0}^{T-1} R_{i,t-m,}R_{j,t-m}$ (T=310,…,784)

5. GARCH : Tri-variate Generalized AutoRegressive Conditional Heteroskedasticity (α's are the MLE by BHHH)

$$\sigma^2_{t+1,i} = \alpha_0 + \alpha_1 R_{t,i}{}^2 + \alpha_2 \sigma^2_{t,i}$$

6. RiskMetrics (Exponentially Weighted Moving Average) : with the predetermined decay factor λ with λ=0.97 , λ=0.94 (by J.P. Morgan) and λ=0.96 (by MLE techniques)

$$\sigma_{i,t+1} = \sqrt{\lambda \sigma^2_{i,t} + (1-\lambda) R^2_{i,t}}$$

$$\sigma_{ij,t+1} = \lambda \sigma_{ij,t} + (1-\lambda) R_{i,t} R_{j,t}$$

6. Implied Volatilities

$$IV_{i,t+1} = \frac{IV_{(annual),i,t}}{\sqrt{52}}$$

and mixed with the HIS-MOV and RM97 correlation forecast method

$$\rho_{ij,t+1} = \frac{\sigma_{ij,t+1}}{\sigma_{i,t+1} \sigma_{j,t+1}}$$

Appendix Two

Parameter Estimations for GARCH

Sample Size	Categories	α (t-value)	α_1 (t-value)	α_2 (t-value)
1-310	Fed Cattle	0.00617 (1.76)	0.928 (2.04)	0.014 (1.77)
1-310	Feeder Cattle	0.00341 (0.70)	0.896 (2.89)	0.023 (1.34)
1-310	Corn	0.0015 (0.85)	0.787 (1.86)	0.208 (2.67)
1-450	Fed Cattle	0.0083 (1.33)	0.0937 (0.39)	0.020 (5.00)
1-450	Feeder Cattle	0.0047 (2.71)	0.904 (2.89)	0.081 (1.34)
1-450	Corn	0.0036 (2.38)	0.823 (15.52)	0.176 (9.70)
1-600	Fed Cattle	0.0079 (1.48)	0.954 (1.73)	0.037 (2.60)
1-600	Feeder Cattle	0.0054 (1.14)	0.908 (3.56)	0.045 (1.32)
1-600	Corn	0.0028 (0.83)	0.847 (2.63)	0.113 (1.01)
1-750	Fed Cattle	0.0096 (0.97)	0.978 (3.08)	0.004 (2.0)
1-750	Feeder Cattle	0.0063 (0.35)	0.917 (0.85)	0.025 (3.76)
1-750	Corn	0.0034 (0.47)	0.853 (11.02)	0.096 2.16)

Appendix Three
Raw Data

Source: LMIC

Cash Prices

WEEK	Fed Steers 1,100 to 1,300 lbs (West Kansas) ($/cwt)	Feeder Steers 600-700 lbs (West Kansas) ($/cwt)	Corn No.2 Yellow Corn (Omaha) ($/bu)	3-Month T-Bill Rate From 01/06/89 (Date / rate in %)
01/05/85	67.25	67.00	2.51	
01/12/85	65.75	67.50	2.50	
01/19/85	65.50	69.62	2.58	
01/26/85	65.50	70.75	2.57	
02/02/85	65.48	70.75	2.56	
02/09/85	65.75	71.50	2.54	
02/16/85	65.12	72.12	2.51	
02/23/85	64.22	69.60	2.49	
03/02/85	62.90	68.75	2.45	
03/09/85	61.65	68.00	2.53	
03/16/85	61.50	68.62	2.51	
03/23/85	60.02	67.00	2.52	
03/30/85	62.20	67.75	2.54	
04/06/85	62.65	66.75	2.34	
04/13/85	61.88	67.38	2.37	
04/20/85	60.20	64.62	2.56	
04/27/85	60.70	64.75	2.55	
05/04/85	60.40	64.75	2.52	
05/11/85	58.55	63.75	2.50	
05/18/85	61.90	66.50	2.44	
05/25/85	61.85	65.00	2.41	
06/01/85	61.12	65.50	2.39	
06/08/85	58.70	63.88	2.43	
06/15/85	60.00	62.75	2.42	
06/22/85	58.80	61.88	2.38	
06/29/85	56.75	61.12	2.35	
07/06/85	56.75	61.88	2.30	
07/13/85	57.15	62.50	2.22	
07/20/85	54.90	60.00	2.24	
07/27/85	52.60	58.75	2.19	
08/03/85	50.90	58.75	2.15	
08/10/85	53.95	62.00	2.15	
08/17/85	54.60	62.12	2.12	
08/24/85	54.15	60.25	2.09	
08/31/85	53.55	61.25	2.05	
09/07/85	53.19	59.75	2.04	
09/14/85	52.05	57.62	2.07	

09/21/85	53.55	58.75	2.08
09/28/85	56.45	61.25	2.15
10/05/85	57.30	61.88	2.31
10/12/85	60.25	61.88	2.24
10/19/85	61.90	61.38	2.25
10/26/85	63.45	62.12	2.29
11/02/85	64.05	62.38	2.29
11/09/85	65.95	64.50	2.34
11/16/85	66.75	63.12	2.35
11/23/85	66.55	62.75	2.43
11/30/85	67.81	62.00	2.49
12/07/85	68.45	64.00	2.51
12/14/85	66.20	61.62	2.48
12/21/85	64.05	60.62	2.45
12/28/85	64.19	61.02	2.46
01/04/86	63.50	61.12	3.75
01/11/86	60.30	62.75	2.37
01/18/86	59.85	64.25	2.33
01/25/86	59.70	63.50	2.29
02/01/86	59.80	64.88	2.20
02/08/86	58.10	63.25	2.17
02/15/86	57.10	62.38	2.13
02/22/86	56.65	62.48	2.15
03/01/86	59.90	63.65	2.13
03/08/86	59.05	62.00	2.15
03/15/86	56.75	59.40	2.15
03/22/86	55.70	60.30	2.14
03/29/86	57.55	63.00	2.16
04/05/86	54.85	59.00	2.21
04/12/86	54.70	57.95	2.23
04/19/86	57.30	56.12	2.17
04/26/86	56.45	53.88	2.14
05/03/86	57.10	57.62	2.20
05/10/86	57.95	54.38	2.19
05/17/86	59.30	56.45	2.15
05/24/86	57.35	53.92	2.16
05/31/86	56.88	55.45	2.08
06/07/86	54.80	53.75	1.96
06/14/86	54.65	52.88	1.97
06/21/86	55.85	57.00	1.83
06/28/86	59.65	60.50	1.81
07/05/86	59.50	60.25	1.80
07/12/86	59.20	61.75	1.80
07/19/86	58.30	61.88	1.78
07/26/86	59.75	63.00	1.74
08/02/86	59.40	62.13	1.73
08/09/86	59.75	64.38	1.79
08/16/86	60.60	65.13	1.78
08/23/86	60.13	66.00	1.69

08/30/86	59.75	64.38	1.67
09/06/86	60.75	66.25	1.68
09/13/86	60.80	66.63	1.70
09/20/86	60.50	64.63	1.83
09/27/86	59.95	65.75	1.90
10/04/86	60.75	64.75	1.92
10/11/86	61.40	64.50	1.97
10/18/86	63.05	64.00	2.05
10/25/86	62.85	63.75	2.07
11/01/86	63.13	63.75	2.02
11/08/86	63.65	64.25	2.00
11/15/86	63.50	64.88	1.99
11/22/86	63.70	66.25	1.95
11/29/86	64.38	63.80	1.96
12/06/86	63.60	65.50	1.86
12/13/86	61.80	64.13	1.80
12/20/86	60.95	64.38	1.78
12/27/86	60.13	62.96	1.78
01/02/87	59.44	62.00	1.95
01/09/87	59.35	65.13	2.03
01/16/87	60.75	66.88	2.05
01/23/87	61.05	66.63	2.09
01/30/87	62.65	71.00	2.13
02/06/87	64.35	71.13	2.16
02/13/87	63.25	69.98	2.13
02/20/87	64.00	71.63	2.08
02/27/87	64.65	72.00	2.08
03/06/87	64.50	71.13	2.08
03/13/87	64.10	69.63	2.09
03/20/87	65.15	70.45	2.11
03/27/87	67.75	70.10	2.13
04/03/87	68.45	70.00	2.12
04/10/87	70.25	72.43	2.11
04/17/87	71.73	72.05	2.12
04/24/87	71.33	71.88	2.09
05/01/87	71.05	72.25	2.18
05/08/87	72.65	74.63	2.14
05/15/87	73.06	72.63	2.21
05/22/87	71.15	71.63	2.19
05/29/87	71.63	70.93	2.08
06/05/87	70.50	74.13	2.04
06/12/87	71.25	76.75	2.07
06/19/87	70.00	76.13	1.96
06/26/87	69.50	76.05	1.95
07/03/87	68.08	76.50	1.91
07/10/87	67.68	76.88	1.98
07/17/87	65.69	78.00	2.00
07/24/87	63.70	75.00	1.96
07/31/87	64.00	75.50	2.00

08/07/87	65.65	78.38	2.03
08/14/87	66.13	78.63	2.05
08/21/87	65.15	82.13	2.08
08/28/87	64.95	82.75	2.00
09/04/87	64.95	83.13	2.04
09/11/87	66.63	86.00	2.04
09/18/87	66.45	80.50	2.05
09/25/87	67.70	83.75	2.08
10/02/87	67.40	80.25	2.11
10/09/87	66.65	80.25	2.13
10/16/87	67.80	83.38	2.13
10/23/87	67.25	78.00	2.13
10/30/87	66.15	74.75	2.10
11/06/87	65.15	75.25	2.10
11/13/87	66.75	78.56	2.15
11/20/87	68.10	80.63	2.15
11/27/87	69.92	82.50	2.16
12/04/87	67.40	82.75	2.16
12/11/87	66.31	81.00	2.16
12/18/87	66.15	80.00	2.16
12/25/87	65.38	80.63	2.12
01/01/88	65.75	81.75	2.14
01/08/88	66.00	85.25	2.17
01/15/88	67.00	85.15	2.18
01/22/88	68.15	83.13	2.14
01/29/88	68.40	84.75	2.15
02/05/88	68.60	82.50	2.14
02/12/88	70.63	84.88	2.13
02/19/88	71.44	86.25	2.13
02/26/88	71.50	85.38	2.15
03/04/88	70.63	82.63	2.15
03/11/88	70.80	85.00	2.09
03/18/88	72.85	83.88	2.10
03/25/88	73.55	84.00	2.06
04/01/88	75.45	83.50	2.04
04/08/88	74.45	83.63	2.04
04/15/88	74.05	84.00	2.08
04/22/88	73.93	85.00	2.14
04/29/88	74.45	85.00	2.14
05/06/88	75.25	82.38	2.13
05/13/88	76.60	84.00	2.14
05/20/88	78.40	85.63	2.15
05/27/88	76.10	83.50	2.21
06/03/88	75.31	83.50	2.50
06/10/88	74.80	84.50	2.82
06/17/88	71.45	76.50	3.04
06/24/88	67.10	72.00	3.11
07/01/88	66.95	74.38	3.99
07/08/88	67.66	74.50	2.93

07/15/88	67.45	78.25	2.70	
07/22/88	65.73	77.13	2.65	
07/29/88	66.83	82.13	2.70	
08/05/88	66.68	81.25	2.70	
08/12/88	69.10	86.00	2.74	
08/19/88	71.35	84.50	2.76	
08/26/88	71.20	83.50	2.72	
09/02/88	72.75	84.00	2.68	
09/09/88	71.47	83.50	2.63	
09/16/88	69.88	84.25	2.59	
09/23/88	68.35	83.50	2.64	
09/30/88	69.95	85.25	2.63	
10/07/88	71.80	84.38	2.63	
10/14/88	72.48	85.13	2.66	
10/21/88	72.70	85.00	2.67	
10/28/88	73.85	86.00	2.74	
11/04/88	72.80	84.63	2.76	
11/11/88	72.95	84.63	2.80	
11/18/88	72.85	83.88	2.82	
11/25/88	72.56	84.75	2.73	
12/02/88	73.73	87.50	2.75	
12/09/88	72.38	87.25	2.75	
12/16/88	73.05	86.50	2.76	
12/23/88	73.95	87.00	2.81	
12/30/88	74.84	86.25	2.77	
01/06/89	74.47	87.63	2.83	8.24
01/13/89	74.58	87.00	2.72	8.36
01/20/89	74.60	85.38	2.69	8.30
01/27/89	73.78	83.63	2.72	8.26
02/03/89	74.55	86.25	2.70	8.33
02/10/89	75.15	86.88	2.70	8.57
02/17/89	75.25	85.75	2.70	8.49
02/24/89	77.00	85.75	2.75	8.51
03/03/89	78.88	83.25	2.79	8.73
03/10/89	78.55	80.50	2.88	8.65
03/17/89	78.80	80.93	2.84	8.69
03/24/89	79.50	83.50	2.87	9.00
03/31/89	79.80	83.88	2.84	9.10
04/07/89	79.40	80.50	2.87	8.87
04/14/89	78.40	79.75	2.82	8.71
04/21/89	77.00	79.00	2.82	8.57
04/28/89	76.05	78.75	2.81	8.66
05/05/89	76.55	80.00	2.80	8.64
05/12/89	76.90	81.50	2.82	8.41
05/19/89	76.10	81.00	2.81	8.21
05/26/89	74.45	81.75	2.63	8.32
06/02/89	72.31	82.88	2.60	8.50
06/09/89	70.75	84.13	2.62	8.17
06/16/89	71.65	87.75	2.55	8.13

06/23/89	72.85	87.88	2.59	8.22
06/30/89	71.70	89.00	2.69	8.07
07/07/89	71.00	89.00	2.63	7.96
07/14/89	70.20	87.50	2.62	7.76
07/21/89	72.00	87.75	2.54	7.87
07/28/89	71.90	87.00	2.49	8.09
08/04/89	71.98	88.50	2.50	7.65
08/11/89	73.95	88.25	2.56	7.94
08/18/89	74.20	89.25	2.58	8.01
08/25/89	73.78	86.88	2.52	7.99
09/01/89	72.63	87.75	2.50	7.94
09/08/89	70.69	85.05	2.32	7.88
09/15/89	68.20	85.88	2.35	7.64
09/22/89	69.05	85.75	2.39	7.64
09/29/89	69.40	85.88	2.37	7.72
10/06/89	69.20	85.25	2.44	7.83
10/13/89	71.05	85.50	2.44	7.63
10/20/89	73.43	85.25	2.51	7.37
10/27/89	74.80	84.75	2.56	7.52
11/03/89	74.73	85.50	2.62	7.78
11/10/89	74.65	85.75	2.68	7.67
11/17/89	75.38	87.50	2.65	7.68
11/24/89	76.06	84.63	2.68	7.61
12/01/89	76.73	87.65	2.75	7.63
12/08/89	76.30	88.38	2.77	7.55
12/15/89	77.28	87.88	2.78	7.60
12/22/89	78.70	87.88	2.77	7.62
12/29/89	79.75	87.88	2.82	7.77
01/05/90	79.69	89.00	2.76	7.64
01/12/90	77.93	85.50	2.78	7.57
01/19/90	77.90	85.50	2.72	7.68
01/26/90	79.40	84.13	2.66	7.66
02/02/90	79.38	83.88	2.61	7.77
02/09/90	79.40	86.55	2.61	7.83
02/16/90	79.05	82.63	2.61	7.65
02/23/90	78.58	82.13	2.59	7.80
03/02/90	77.38	83.75	2.59	7.72
03/09/90	78.43	83.50	2.63	7.85
03/16/90	80.05	86.13	2.65	7.96
03/23/90	80.05	85.00	2.63	7.97
03/30/90	79.85	86.50	2.68	7.85
04/06/90	80.33	86.25	2.66	7.83
04/13/90	80.85	86.13	2.67	7.80
04/20/90	80.70	88.13	2.67	7.71
04/27/90	79.13	86.60	2.71	7.78
05/04/90	78.55	89.88	2.72	7.91
05/11/90	79.30	90.75	2.71	7.79
05/18/90	78.88	90.88	2.67	7.67
05/25/90	78.15	92.75	2.76	7.74

06/01/90	77.31	92.00	2.75	7.80
06/08/90	76.98	92.25	2.75	7.69
06/15/90	77.23	90.50	2.75	7.73
06/22/90	77.40	91.00	2.72	7.74
06/29/90	75.33	91.63	2.67	7.78
07/06/90	74.16	90.87	2.62	7.73
07/13/90	74.06	90.38	2.54	7.81
07/20/90	75.73	92.50	2.46	7.62
07/27/90	77.15	95.13	2.36	7.49
08/03/90	77.38	96.88	2.33	7.50
08/10/90	77.63	95.48	2.40	7.23
08/17/90	78.80	96.00	2.46	7.41
08/24/90	77.90	93.38	2.47	7.55
08/31/90	76.55	90.95	2.46	7.49
09/07/90	75.94	89.88	2.45	7.39
09/14/90	77.95	92.88	2.46	7.41
09/21/90	79.33	93.53	2.51	7.39
09/28/90	79.50	90.45	2.54	7.32
10/05/90	80.25	90.28	2.51	7.18
10/12/90	79.44	93.00	2.47	7.19
10/19/90	79.55	90.78	2.52	7.18
10/26/90	80.45	92.50	2.64	7.20
11/02/90	81.25	90.50	2.63	7.12
11/09/90	80.98	90.38	2.63	7.07
11/16/90	81.50	90.50	2.61	7.05
11/23/90	82.22	91.25	2.64	7.08
11/30/90	81.95	92.50	2.66	7.02
12/07/90	80.75	93.50	2.58	7.06
12/14/90	81.85	92.50	2.60	6.86
12/21/90	81.35	93.88	2.61	6.78
12/28/90	81.16	92.89	2.63	6.52
01/04/91	80.75	93.75	2.72	6.52
01/11/91	80.25	95.88	2.69	6.52
01/18/91	78.35	91.13	2.66	6.12
01/25/91	78.95	95.00	2.69	6.14
02/01/91	79.60	94.13	2.67	6.22
02/08/91	79.73	94.88	2.73	5.97
02/15/91	79.50	95.00	2.69	5.86
02/22/91	79.80	93.88	2.71	5.94
03/01/91	80.40	96.13	2.75	6.01
03/08/91	81.45	95.63	2.75	6.09
03/15/91	82.25	95.63	2.77	5.85
03/22/91	81.55	96.63	2.84	5.83
03/29/91	80.40	98.75	2.82	5.86
04/05/91	82.05	98.50	2.81	5.80
04/12/91	81.88	97.25	2.83	5.60
04/19/91	80.78	98.88	2.90	5.57
04/26/91	80.25	97.25	2.91	5.69
05/03/91	80.33	96.88	2.82	5.60

05/10/91	79.53	97.00	2.88	5.50
05/17/91	78.50	96.75	2.86	5.50
05/24/91	77.25	99.25	2.75	5.50
05/31/91	77.75	97.75	2.81	5.46
06/07/91	76.60	99.75	2.69	5.59
06/14/91	75.05	99.00	2.76	5.60
06/21/91	74.08	96.25	2.74	5.61
06/28/91	72.38	94.50	2.64	5.58
07/05/91	72.56	96.50	2.50	5.59
07/12/91	73.05	93.88	2.45	5.58
07/19/91	73.00	94.75	2.50	5.56
07/26/91	72.70	94.38	2.44	5.60
08/02/91	69.93	94.63	2.50	5.58
08/09/91	65.65	92.13	2.31	5.51
08/16/91	65.75	91.56	2.44	5.30
08/23/91	69.55	89.13	2.54	5.17
08/30/91	68.40	90.50	2.50	5.40
09/06/91	67.06	88.88	2.47	5.34
09/13/91	68.70	92.25	2.52	5.29
09/20/91	68.75	90.38	2.55	5.19
09/27/91	72.20	89.13	2.57	5.18
10/04/91	72.30	89.63	2.55	5.11
10/11/91	70.25	88.75	2.58	5.04
10/18/91	71.25	85.13	2.69	4.99
10/25/91	71.60	85.25	2.69	5.04
11/01/91	69.25	86.50	2.68	4.99
11/08/91	69.65	84.75	2.68	4.74
11/15/91	72.80	85.50	2.67	4.64
11/22/91	73.70	86.75	2.68	4.58
11/29/91	72.81	86.75	2.70	4.44
12/06/91	71.83	84.63	2.72	4.39
12/13/91	71.15	83.00	2.73	4.21
12/20/91	69.35	80.00	2.73	4.14
12/27/91	68.63	81.23	2.71	3.75
01/03/92	70.50	81.65	2.67	3.91
01/10/92	72.70	81.76	2.68	3.85
01/17/92	74.90	83.57	2.63	3.83
01/24/92	74.45	81.88	2.65	3.78
01/31/92	74.80	82.94	2.69	3.84
02/07/92	76.30	84.88	2.67	3.86
02/14/92	78.35	84.44	2.71	3.72
02/21/92	77.60	84.07	2.72	3.83
02/28/92	76.35	82.19	2.68	3.96
03/06/92	77.00	84.00	2.70	4.02
03/13/92	79.35	82.57	2.67	4.02
03/20/92	78.50	83.00	2.71	4.09
03/27/92	78.10	81.38	2.73	4.08
04/03/92	79.00	84.26	2.70	4.08
04/10/92	79.50	84.44	2.63	3.95

04/17/92	77.95	82.57	2.68	3.60
04/24/92	76.60	81.82	2.62	3.69
05/01/92	76.80	79.63	2.62	3.71
05/08/92	77.15	79.88	2.66	3.65
05/15/92	77.15	82.13	2.62	3.64
05/22/92	75.23	81.44	2.59	3.61
05/29/92	73.75	82.25	2.63	3.75
06/05/92	73.65	84.38	2.68	3.75
06/12/92	74.20	86.63	2.70	3.71
06/19/92	73.95	86.75	2.79	3.66
06/26/92	72.43	86.19	2.76	3.67
07/03/92	72.84	85.00	2.76	3.59
07/10/92	72.65	86.07	2.64	3.23
07/17/92	73.95	85.38	2.67	3.22
07/24/92	72.88	84.88	2.63	3.16
07/31/92	72.10	87.13	2.51	3.18
08/07/92	73.55	87.19	2.49	3.20
08/14/92	74.65	87.63	2.51	3.13
08/21/92	74.35	88.25	2.53	3.10
08/28/92	74.53	86.97	2.58	3.14
09/04/92	73.65	87.66	2.52	3.17
09/11/92	74.56	89.44	2.53	2.91
09/18/92	75.70	88.75	2.51	2.89
09/25/92	75.55	87.88	2.53	2.91
10/02/92	75.38	85.57	2.47	2.73
10/09/92	75.45	86.63	2.51	2.67
10/16/92	76.60	85.50	2.54	2.88
10/23/92	76.48	85.44	2.45	2.94
10/30/92	75.80	85.13	2.45	2.97
11/06/92	75.05	85.01	2.45	3.05
11/13/92	74.75	86.57	2.46	3.10
11/20/92	75.75	87.19	2.46	3.13
11/27/92	76.75	85.64	2.51	3.27
12/04/92	77.33	82.07	2.51	3.31
12/11/92	77.65	85.19	2.50	3.29
12/18/92	78.68	86.75	2.52	3.26
12/25/92	77.94	87.25	2.49	3.16
01/01/93	77.19	88.38	2.53	3.22
01/08/93	77.95	90.88	2.55	3.15
01/15/93	80.45	90.28	2.57	3.07
01/22/93	80.70	90.50	2.58	3.03
01/29/93	79.16	87.88	2.58	2.98
02/05/93	78.40	89.13	2.60	2.97
02/12/93	80.44	86.44	2.52	2.94
02/19/93	81.31	85.00	2.54	2.93
02/26/93	80.35	85.88	2.55	2.96
03/05/93	79.85	85.00	2.56	2.97
03/12/93	80.95	87.38	2.55	2.98
03/19/93	83.10	89.69	2.54	3.00

03/26/93	85.35	91.75	2.53	2.94
04/02/93	83.30	90.82	2.51	2.96
04/09/93	81.75	90.32	2.50	2.92
04/16/93	82.45	93.13	2.49	2.89
04/23/93	81.75	94.50	2.48	2.82
04/30/93	82.18	93.88	2.48	2.88
05/07/93	82.40	93.63	2.48	2.88
05/14/93	82.25	94.01	2.47	2.89
05/21/93	80.63	96.88	2.45	3.00
05/28/93	78.25	92.15	2.45	3.06
06/04/93	76.50	92.32	2.44	3.08
06/11/93	78.35	93.82	2.44	3.14
06/18/93	77.90	94.94	2.45	3.07
06/25/93	76.00	91.82	2.47	3.10
07/02/93	75.78	95.00	2.46	3.05
07/09/93	75.66	91.69	2.49	3.01
07/16/93	73.65	92.63	2.51	3.04
07/23/93	72.55	89.38	2.43	3.05
07/30/93	74.35	90.88	2.53	3.10
08/06/93	75.80	91.13	2.52	3.10
08/13/93	76.38	92.57	2.43	3.05
08/20/93	75.05	92.94	2.38	3.03
08/27/93	73.60	88.38	2.34	3.02
09/03/93	74.00	89.69	2.22	3.02
09/10/93	75.13	92.13	2.16	2.95
09/17/93	74.40	89.94	2.15	2.98
09/24/93	72.50	89.88	2.15	2.93
10/01/93	71.15	87.50	2.13	2.90
10/08/93	71.23	87.88	2.15	2.96
10/15/93	69.90	85.50	2.17	3.04
10/22/93	72.85	86.13	2.22	3.06
10/29/93	74.25	87.25	2.30	3.08
11/05/93	73.15	87.50	2.31	3.11
11/12/93	72.90	85.75	2.39	3.11
11/19/93	73.75	85.38	2.45	3.11
11/26/93	72.75	85.13	2.55	3.14
12/03/93	71.70	86.13	2.51	3.12
12/10/93	71.23	83.19	2.56	3.11
12/17/93	72.65	84.75	2.55	3.06
12/24/93	73.63	85.82	2.55	3.06
12/31/93	72.13	88.50	2.61	3.06
01/07/94	71.78	86.44	2.51	3.10
01/14/94	73.35	86.63	2.56	3.02
01/21/94	73.53	85.07	2.55	2.99
01/28/94	72.35	83.82	2.51	2.96
02/04/94	71.95	84.19	2.54	2.99
02/11/94	71.35	84.13	2.50	3.24
02/18/94	73.80	87.13	2.75	3.28
02/25/94	74.25	83.94	2.48	3.33

03/04/94	75.60	87.38	2.44	3.40
03/11/94	75.60	86.38	2.44	3.52
03/18/94	75.60	85.94	2.48	3.57
03/25/94	75.15	86.19	2.43	3.61
04/01/94	75.45	86.38	2.45	3.50
04/08/94	76.75	87.07	2.45	3.71
04/15/94	76.60	85.88	2.43	3.63
04/22/94	74.75	86.88	2.42	3.76
04/29/94	74.05	85.50	2.43	3.85
05/06/94	71.35	84.50	2.42	4.00
05/13/94	69.80	84.32	2.43	4.32
05/20/94	67.58	82.19	2.43	4.22
05/27/94	64.55	78.51	2.38	4.23
06/03/94	66.25	80.44	2.44	4.23
06/10/94	64.20	78.25	2.47	4.15
06/17/94	64.50	75.00	2.45	4.16
06/24/94	63.10	77.19	2.39	4.18
07/01/94	60.45	76.19	2.39	4.20
07/08/94	61.19	77.88	2.35	4.31
07/15/94	67.30	81.65	2.35	4.50
07/22/94	69.10	83.40	2.34	4.31
07/29/94	66.85	82.93	2.31	4.43
08/05/94	69.45	83.57	2.40	4.35
08/12/94	70.00	82.25	2.41	4.43
08/19/94	68.17	81.07	2.42	4.59
08/26/94	65.60	79.57	2.42	4.62
09/02/94	66.65	76.63	2.41	4.61
09/09/94	67.56	75.38	2.43	4.58
09/16/94	66.85	78.13	2.47	4.61
09/23/94	66.30	76.38	2.47	4.61
09/30/94	66.50	74.63	2.49	4.79
10/07/94	65.45	76.13	2.49	4.92
10/14/94	65.15	74.00	2.49	4.92
10/21/94	65.70	74.51	2.49	4.92
10/28/94	69.40	74.94	2.46	5.07
11/04/94	69.38	76.32	2.50	5.07
11/11/94	69.70	77.13	2.50	5.25
11/18/94	69.75	76.32	2.51	5.29
11/25/94	69.75	75.00	2.52	5.40
12/02/94	67.56	76.69	2.50	5.44
12/09/94	67.83	76.75	2.51	5.83
12/16/94	69.75	78.19	2.51	5.76
12/23/94	69.75	78.13	2.52	5.59
12/30/94	70.00	79.75	2.51	5.56
01/06/95	72.63	80.05	2.50	5.78
01/13/95	72.75	78.56	2.52	5.87
01/20/95	73.40	77.88	2.50	5.77
01/27/95	74.30	77.83	2.49	5.80
02/03/95	73.60	76.58	2.53	5.79

02/10/95	73.00	75.63	2.52	5.83
02/17/95	74.40	75.14	2.51	5.82
02/24/95	73.40	73.39	2.54	5.74
03/03/95	73.45	73.02	2.54	5.73
03/10/95	73.25	72.59	2.55	5.77
03/17/95	71.00	70.67	2.56	5.76
03/24/95	68.75	72.38	2.56	5.76
03/31/95	66.40	70.48	2.60	5.64
04/07/95	69.33	71.35	2.60	5.76
04/14/95	67.75	69.93	2.63	5.70
04/21/95	65.85	68.54	2.76	5.56
04/28/95	67.40	68.83	2.86	5.66
05/05/95	66.75	66.76	2.90	5.74
05/12/95	63.50	64.91	2.94	5.63
05/19/95	62.75	67.25	3.04	5.71
05/26/95	63.85	67.68	3.02	5.72
06/02/95	63.00	70.50	3.04	5.64
06/09/95	64.55	70.92	3.02	5.48
06/16/95	64.50	71.67	3.08	5.57
06/23/95	63.17	71.42	3.10	5.46
06/30/95	63.00	68.94	3.11	5.35
07/07/95	63.00	69.20	2.95	5.53
07/14/95	61.85	67.40	3.22	5.40
07/21/95	60.30	67.13	3.12	5.46
07/28/95	61.10	66.57	2.97	5.47
08/04/95	63.35	68.97	2.81	5.44
08/11/95	63.35	68.10	2.83	5.41
08/18/95	61.69	65.86	2.82	5.42
08/25/95	60.53	65.39	2.82	5.43
09/01/95	59.95	64.16	2.82	5.34
09/08/95	63.50	66.43	2.89	5.30
09/15/95	63.75	66.39	2.98	5.34
09/22/95	64.00	65.90	3.22	5.25
09/29/95	64.40	65.65	3.34	5.14
10/06/95	63.00	63.02	3.43	5.34
10/13/95	64.50	65.18	3.45	5.31
10/20/95	65.60	62.75	3.67	5.32
10/27/95	66.00	64.60	3.75	5.22
11/03/95	67.15	64.12	3.91	5.29
11/10/95	68.00	65.85	3.85	5.36
11/17/95	68.75	64.04	3.78	5.43
11/24/95	67.75	63.22	3.69	5.34
12/01/95	67.60	65.37	3.75	5.32
12/08/95	67.30	64.94	3.84	5.29
12/15/95	66.20	62.48	3.85	5.30
12/22/95	66.00	61.73	3.88	5.15
12/29/95	64.75	61.36	3.95	4.91
01/05/96	65.00	58.23	3.92	5.04
01/12/96	64.10	59.93	3.84	5.03

01/19/96	65.00	58.97	3.80	5.02
01/26/96	63.00	57.03	3.76	4.99
02/02/96	62.40	56.04	3.76	5.01
02/09/96	63.00	57.72	3.85	4.88
02/16/96	63.00	57.56	3.84	4.80
02/23/96	63.00	57.83	3.82	4.78
03/01/96	62.80	57.29	3.68	4.86
03/08/96	60.90	56.16	3.64	4.89
03/15/96	61.40	56.10	3.53	4.95
03/22/96	63.00	56.22	3.67	5.02
03/29/96	62.00	54.98	3.69	4.99
04/05/96	62.00	55.64	3.90	5.07
04/12/96	60.70	51.79	3.83	5.03
04/19/96	58.55	51.77	3.91	4.87
04/26/96	55.40	51.08	3.78	4.97
05/03/96	57.25	53.47	3.93	5.00
05/10/96	61.00	57.74	3.88	5.02
05/17/96	60.00	58.16	4.01	5.02
05/24/96	59.00	57.66	3.99	5.03
05/31/96	59.44	59.52	3.93	5.03
06/07/96	61.75	60.45	3.94	5.09
06/14/96	62.80	59.18	4.06	5.16
06/21/96	61.15	58.90	3.82	5.08
06/28/96	60.20	60.66	3.71	5.10
07/05/96	62.50	61.14	3.75	5.12
07/12/96	64.40	60.09	3.20	5.21
07/19/96	65.00	60.76	3.19	5.19
07/26/96	63.65	61.18	3.17	5.14
08/02/96	62.50	63.60	3.20	5.20
08/09/96	65.70	65.27	3.29	5.08
08/16/96	66.00	63.48	3.32	5.04
08/23/96	67.88	64.00	3.12	5.06
08/30/96	68.40	63.30	3.04	5.07
09/06/96	69.40	63.78	2.98	5.19
09/13/96	71.00	65.70	2.92	5.17
09/20/96	72.00	64.85	2.93	5.07
09/27/96	72.00	61.61	2.83	5.18
10/04/96	72.45	64.06	2.80	5.01
10/11/96	71.40	61.10	2.75	4.96
10/18/96	70.00	61.47	2.75	5.01
10/25/96	70.00	61.58	2.67	5.01
11/01/96	70.80	60.01	2.62	5.04
11/08/96	71.60	65.22	2.67	5.04
11/15/96	72.15	64.76	2.75	5.02
11/22/96	70.08	65.57	2.77	5.03
11/29/96	67.88	63.75	2.71	5.03
12/06/96	67.70	64.49	2.77	4.98
12/13/96	65.33	65.19	2.83	4.83
12/20/96	65.00	65.49	2.87	4.76

12/27/96	65.50	67.01	2.87	4.92
01/03/97	66.00	68.25	2.90	5.08
01/10/97	64.90	69.97	2.90	5.02
01/17/97	65.80	69.58	2.88	5.04
01/24/97	64.95	71.30	2.83	5.03
01/31/97	64.15	70.98	2.80	5.06
02/07/97	63.00	71.77	2.70	5.00
02/14/97	63.60	73.21	2.83	5.02
02/21/97	65.67	71.25	2.78	4.98
02/28/97	68.75	73.12	2.83	5.01
03/07/97	68.00	72.15	2.86	5.10
03/14/97	67.60	74.22	2.88	5.06
03/21/97	67.33	73.03	2.89	5.13
03/28/97	67.00	72.69	2.84	5.26
04/04/97	67.00	73.83	2.82	5.18
04/11/97	66.50	78.81	2.83	5.14
04/18/97	68.67	78.78	2.85	5.15
04/25/97	67.60	79.29	2.92	5.21
05/02/97	68.00	78.17	2.90	5.22
05/09/97	68.80	79.65	2.93	5.14
05/16/97	67.56	81.52	2.90	5.08
05/23/97	66.55	79.71	2.83	5.17
05/30/97	65.40	80.21	2.80	5.03
06/06/97	63.75	83.44	2.78	4.93
06/13/97	63.00	83.08	2.69	4.94
06/20/97	64.00	84.46	2.68	4.88
06/27/97	63.00	82.68	2.54	4.94
07/04/97	63.00	86.88	2.48	5.12
07/11/97	61.70	85.18	2.52	4.97
07/18/97	63.75	87.81	2.53	5.05
07/25/97	63.75	85.19	2.54	5.11
08/01/97	66.00	85.94	2.48	5.12
08/08/97	64.60	84.49	2.50	5.15
08/15/97	64.60	83.51	2.56	5.17
08/22/97	66.00	83.89	2.63	5.08
08/29/97	64.33	83.30	2.73	5.12
09/05/97	64.50	83.57	2.75	5.07
09/12/97	67.00	84.34	2.77	5.01
09/19/97	66.70	80.89	2.72	4.91
09/26/97	66.00	84.48	2.73	4.90
10/03/97	65.80	76.49	2.77	4.93
10/10/97	65.00	80.64	2.76	4.93
10/17/97	65.75	80.06	2.75	4.98
10/24/97	68.25	80.25	2.70	4.96
10/31/97	70.00	77.61	2.73	4.97
11/07/97	68.67	77.64	2.67	5.12
11/14/97	67.50	76.00	2.63	5.16
11/21/97	66.88	76.93	2.64	5.17
11/28/97	67.00	76.44	2.62	5.15

12/05/97	66.25	77.09	2.60	5.11
12/12/97	66.00	80.55	2.52	5.15
12/19/97	65.00	78.75	2.52	5.07
12/26/97	66.00	76.01	2.49	5.30
01/02/98	66.00	75.50	2.45	5.29
01/09/98	64.56	78.42	2.45	5.12
01/16/98	63.95	83.37	2.46	4.97
01/23/98	64.97	83.10	2.45	4.98
01/30/98	63.15	80.61	2.44	5.07
02/06/98	61.23	79.48	2.39	5.10
02/13/98	60.04	80.97	2.36	5.10
02/20/98	61.95	82.14	2.28	5.08
02/27/98	59.41	81.03	2.25	5.14
03/06/98	60.94	81.23	2.24	5.12
03/13/98	62.94	80.87	2.15	4.97
03/20/98	63.00	79.54	2.13	4.99
03/27/98	61.80	79.45	2.08	5.03
04/03/98	61.92	80.56	2.04	5.05
04/10/98	65.87	83.25	1.98	4.96
04/17/98	65.92	84.57	2.01	5.04
04/24/98	64.06	82.14	2.01	4.99
05/01/98	65.94	75.04	2.04	4.94
05/08/98	66.00	80.28	2.08	4.99
05/15/98	65.13	82.54	2.16	5.01
05/22/98	63.99	84.50	2.18	5.08
05/29/98	63.03	79.07	2.20	5.02
06/05/98	63.89	78.79	2.12	4.95
06/12/98	64.96	79.13	2.14	5.00
06/19/98	63.99	76.17	2.20	5.01
06/26/98	62.91	74.20	2.04	4.99
07/03/98	62.04	73.92	2.06	5.00
07/10/98	60.99	71.56	2.06	4.96
07/17/98	59.97	75.25	2.02	4.98
07/24/98	59.35	72.03	2.00	4.95
07/31/98	59.01	68.24	1.94	4.92
08/07/98	59.75	68.99	1.92	4.98
08/14/98	59.98	69.65	1.90	4.94
08/21/98	59.01	69.75	1.68	4.91
08/28/98	57.18	69.20	1.58	4.92
09/04/98	56.36	67.85	1.55	4.80
09/11/98	57.91	68.25	1.59	4.79
09/18/98	59.99	70.51	1.65	4.74
09/25/98	59.07	71.68	1.76	4.64
10/02/98	57.25	68.69	1.81	4.43
10/09/98	58.89	67.05	1.86	4.16
10/16/98	62.32	70.10	1.89	3.91
10/23/98	63.02	70.41	1.91	3.85
10/30/98	63.95	70.33	1.90	4.07
11/06/98	63.30	69.04	1.94	4.43

11/13/98	63.00	70.25	1.98	4.47
11/20/98	60.98	69.64	2.03	4.40
11/27/98	61.67	69.19	2.07	4.45
12/04/98	61.73	69.84	2.10	4.44
12/11/98	61.04	70.26	2.07	4.32
12/18/98	57.92	66.70	2.07	4.39
12/25/98	57.96	65.00	2.06	4.44
01/01/99	59.86	69.69	2.04	4.52
01/08/99	60.99	75.13	2.05	4.38
01/15/99	61.96	75.61	2.02	4.39
01/22/99	60.82	76.71	2.04	4.28
01/29/99	61.35	75.45	2.08	4.31
02/05/99	60.04	73.75	2.13	4.40
02/12/99	62.02	77.00	2.08	4.42
02/19/99	63.41	78.92	1.99	4.44
02/26/99	63.04	76.39	2.04	4.53
03/05/99	64.98	77.61	2.04	4.57
03/12/99	65.96	77.68	2.03	4.51
03/19/99	65.17	74.64	1.97	4.47
03/26/99	64.37	76.56	1.98	4.38
04/02/99	64.97	76.82	1.92	4.38
04/09/99	65.00	76.01	1.86	4.27
04/16/99	65.68	75.90	1.87	4.19
04/23/99	65.08	76.37	1.89	4.23
04/30/99	66.00	75.87	2.04	4.34
05/07/99	65.05	75.70	1.94	4.48
05/14/99	63.93	77.43	1.92	4.48
05/21/99	64.99	78.27	1.92	4.57
05/28/99	65.86	80.33	1.93	4.50
06/04/99	66.01	77.13	1.93	4.62
06/11/99	66.97	79.91	1.96	4.51
06/18/99	67.01	81.25	2.02	4.62
06/25/99	65.91	78.22	2.05	4.61
07/02/99	64.01	85.00	1.98	4.75
07/09/99	63.28	77.10	2.01	4.59
07/16/99	64.01	82.80	2.03	4.60
07/23/99	64.56	82.47	2.01	4.52
07/30/99	65.04	79.79	2.09	4.54
08/06/99	64.97	78.69	2.02	4.70
08/13/99	65.00	79.37	2.04	4.79
08/20/99	65.00	78.50	2.04	4.68
08/27/99	65.52	81.59	2.04	4.85
09/03/99	65.97	81.51	2.10	4.88
09/10/99	65.99	82.73	2.11	4.72
09/17/99	66.03	84.64	2.13	4.66
09/24/99	65.51	80.04	2.18	4.66
10/01/99	66.82	82.17	2.15	4.72
10/08/99	68.31	81.76	2.12	4.73
10/15/99	70.70	83.63	2.11	4.78

10/22/99	70.32	81.96	2.05	4.99
10/29/99	69.21	78.75	2.07	5.00
11/05/99	69.29	81.86	2.06	5.00
11/12/99	69.81	84.12	2.04	5.03
11/19/99	70.79	85.65	2.03	5.12
11/26/99	70.93	87.13	2.03	5.11
12/03/99	69.88	87.85	1.98	5.20
12/10/99	69.94	88.19	1.96	5.05
12/17/99	68.74	89.69	2.00	5.21
12/24/99	68.00	88.17	2.08	5.40
12/31/99	68.00	84.81	2.13	5.30

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