Agricultural Applications of Value-at-Risk Analysis: A Perspective

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ABSTRACT

Value-at-Risk (VaR) determines the probability of a portfolio of assets losing a certain amount in a given time period due to adverse market conditions with a particular level of confidence. Value-at-Risk has received considerable attention from financial economists and financial practitioners for its use in risk reporting, in particular the risks of derivatives. This paper provides a "state-of-the-art" review of VaR estimation techniques and empirical findings found in the finance literature. The ability of VaR estimates to represent large losses associated with tail events varies among procedure, confidence level, and data used. To date, there is no consensus to the most appropriate estimation technique. Potential applications of Value-at-Risk are suggested in the context of agricultural risk management. In the wake of the Hedge-to-Arrive crisis, the lifting of agricultural trade options by the CFTC, and the decreased government participation, VaR seems to have a place in the agricultural risk manager's toolkit.

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INTRODUCTION

Value-at-Risk (VaR) measures are used to estimate the probability of a portfolio of assets losing more than a specified amount over a specified time period due to adverse movements in the underlying market factors of a portfolio. For example, a Value-at-Risk measure of 1 million dollars at the 95% level of confidence implies that overall portfolio losses would not exceed 1 million dollars more than 5% of the time over a given holding period under normal market conditions (Linsmeier and Pearson, 1996 and 1997; Jorion 1996 and 1997; Mahoney; JP Morgan *Risk Metrics*). Currently, Value-at-Risk is being touted as the "state-of-the-art" in measuring the risks associated with a portfolio of assets, in particular derivatives positions. In essence, Value-at-Risk estimates attempt to capture extreme events that occur in the lower tail of the portfolio's return distribution.

The recent explosion of interest in Value-at-Risk stems from its use in risk disclosure and risk reporting. In the wake of several well publicized derivatives debacles, such as the Barrings Bank failure, several regulatory bodies have recommended or mandated the reporting of VaR estimates by firms (i.e. large trading banks) that maintain large derivatives positions in order to provide a clear, foreword looking measure of a firm's downside risk potential associated with derivative positions. Most notably, in January of 1997 the Securities and Exchange Commission (SEC) established rules for the quantitative and qualitative reporting of risks associated with highly market sensitive assets (i.e., derivatives positions) of reporting firms. Value-at-Risk was one of only 3 quantitative risk reporting methods approved for use in SEC disclosures.[1] Similarly, futures exchanges use VaR to measure the probability of default by clearing members (Fuhrman). Due to VaR's emphasis on downside risk, it is considered by many to be a more intuitive measure of risk and more easily understood by top level managers and outside investors who may or may not be well trained in statistical methods.

As a result of the interest in Value-at-Risk, an entire industry has evolved devoted to the implementation and use of VaR primarily through seminars and the development and sale of software designed to calculate the risk measure. Much of this can be attributed to JP Morgan's publication on the World Wide Web of their *Risk Metrics* system for developing Value-at-Risk measures (*http://www.jpmorgan.com/RiskManagement/RiskMetrics/pubs.html*). By doing this, JP Morgan has attempted to position their estimation methodology as the industry standard for computing Value-at-Risk. In addition to the work of JP Morgan, there is an entire World Wide Web page devoted to all facets of the topic of Value-at-Risk, which has become a well known clearinghouse for research and discussion regarding the risk measure (*http://pw2.netcom.com/~bschact/varbiblio.html*).

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[1]Linsmeier and Pearson (1997) provide an excellent discussion concerning the rules put forth by the SEC for disclosure of market risk sensitive instruments.

Despite the obvious uses of VaR for risk disclosure purposes, Value-at-Risk has also been suggested for firm level risk management. VaR could be beneficial in making hedging decisions, managing cash flows, setting position limits, and overall portfolio selection and allocation. VaR also has several potential applications in agricultural economics. The Ag-Risk program developed by The Ohio State University and the University of Illinois at Urbana-Champaign uses Value-at-Risk analysis in determining the potential downside revenue that could be realized by implementing (or not implementing) alternative pre-harvest marketing strategies for corn, wheat, and soybeans (see Ag-Risk at http://www.agecon.ag.ohio-state.edu/agrisk/agrisk.htm). At a CFTC hearing regarding the lifting of the ban on agricultural trade options for certain enumerated commodities, VaR was recommended for use in reporting the market risk associated with such contracts.[2] This, along with continued volatility of agricultural prices implies several applications of VaR in agricultural economics.

This review paper will present the "state of the art" concerning Value-at-Risk, particularly as it is presented in the finance literature. In doing this, a theoretical definition of VaR will first be presented linking VaR to traditional measures of volatility, followed by current research on the topic. Much of the recent literature on the use of VaR can be considered "survey orientated" presenting the potential pro's and con's of various estimation techniques, thus providing an *a-priori* evaluation of how these models may perform under alternative portfolio conditions. Special attention will also be given to empirical evidence concerning the ability of VaR estimates to measures tail behavior. From results and implications drawn from the literature review, extensions of VaR for use in agricultural risk management and related research topics are presented.

THEORETICAL CONSTRUCTS OF VALUE-AT-RISK

Jorion (1996, 1997) defines VaR for a general class of distributions such that end-of-period portfolio value is $W=W_o(1+R)$ where W_o is the initial investment and R is the rate of return on the portfolio. Subsequently, Jorion (1996, 1997) defines critical end-of-period portfolio value as W^* where $W^*=W_o(1+R^*)$, W_o 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) under normal market conditions[3]. For a specified confidence level (c) and a general distribution of future portfolio value *f(W)*, Jorion (1996, 1997) defines VaR as:

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[2]This was one of two CFTC public hearings on the topic of lifting the ban on agricultural trade options. This particular meeting was held in July 1998 in Bloomington, IL.

[3] The 95% and 99% confidence levels are the most common confidence levels used in VaR analysis.

(1) $$1 - c = \int_{-\infty}^{W^*} f(W)\,dw$$

thus isolating the area in the left tail of the distribution. 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 Value-at-Risk of the portfolio.

By assuming the general distribution of portfolio value, f(W) in equation (1), is the standard normal distribution $f(\epsilon)$ where $\epsilon \sim (0,1)$ and normalizing (R^*-μ) Jorion (1996, 1997) defines a normal deviate (α) as:

(2) $$-\alpha = \frac{-|R^*| - \mu}{\sigma}.$$

Associating the normal deviate (α) with R*, Jorion (1996, 1997) shows that

(3) $$1 - c = \int_{-\infty}^{W^*} f(W)\,dw = \int_{-\infty}^{-|R^*|} f(R)\,dR = \int_{-\infty}^{-\alpha} f(\varepsilon)\,d\varepsilon.$$

From the equality in equation (3), Jorion (1997, p. 89) states "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 deviate α can be found. For instance, at the 95% confidence level, 1-c = 5%. Therefore, the associated α corresponding to the lower 5% of the normal distribution is equal to 1.65. Jorion (1996, p. 49) notes that equation (3) provides an illustrative linkage that shows "VaR may be found in terms of portfolio value (W*), cutoff return (R*), or normal deviate (α)." Therefore, VaR under the assumption of normality is :

(4) $$VaR_{\mu} = W_0 \alpha\sigma$$

where W_0 is defined as before to be initial portfolio value, α 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 percentile 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 subsequently portfolio volatility.

VALUE-AT-RISK ESTIMATION

Techniques used to generate Value-at-Risk measures are not novel. As shown above, Value-at-Risk 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 is much debate over the best method.

Parametric Estimates of VaR: The Delta-Normal Method

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 (Hendricks, Jorion, 1996, 1997; Boudoukh et al.), implied volatility from options prices (Jorion, 1996, 1997; Hopper; Mahoney), various conditional time series models (Jorion 1996, 1997; JP Morgan *Risk Metrics*; Hendricks; Hopper; Duffie and Pan), and regime switching models (Duffie and Pan; Venkataraman) have all been suggested for use in delta-normal VaR. Much of the interest in parametric models of VaR has been motivated by the efforts of JP Morgan and the dissemination of their *Risk Metrics* methodology for developing estimates of standard deviation and correlation among portfolio assets using an exponentially weighted average approach. Outside the context of VaR, these methods for estimating volatility have 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.[4] Due to the onslaught of interest in VaR, there is now added motivation for accurate volatility forecasts (Boudoukh, et al.).

Delta-normal VaR has been praised for its ability to incorporate time-varying volatility through the use of ARCH type models, using simple moving averages, or exponentially weighted moving average such as JP Morgan's *Risk Metrics* procedure. 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; JP Morgan *Risk Metrics*; and Mahoney stated the opposite. This would seem to be an issue solved on the basis of a individual manager's skill and familiarity with statistical methods.

[4]See Figlewski for an excellent survey concerning volatility forecasting and Bollerslev et al. for a thorough review of GARCH applications to financial data.

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 distributions, such as the Student's t-distribution, when fat tails are encountered, maintaining use of standard deviations.

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 causes in delta-normal VaR models. The normality assumption also becomes problematic when portfolios contain options positions causing 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; JP Morgan *Risk Metrics*).

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 Value-at-Risk 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, (p. 4) "scaling is misleading and tends to produce spurious magnification of volatility fluctuations with horizon." Christoffersen and Diebold and Diebold, et al. note that scaling up volatility is only valid under the assumption that returns are distributed *iid*.

Full-Valuation Procedures

The full-valuation procedures that have been suggested for use in developing VaR estimates include simple historical simulation (Mahoney; Butler and Schachter), full Monte Carlo simulation (Jorion, 1997; Linsmeier and Pearson, 1996, 1997), and bootstrapping methods (Jorion, 1997; Duffie and Pan; Sortino and Forsey). Full-valuation procedures, often called non-parametric VaR, attempt to model the entire return distribution instead of providing a point estimate of volatility.[5]

Historical simulation, the most simplistic of the full-valuation procedures, exposes the portfolio positions to past observations of the risky positions over a given historical period. For instance, with fixed weights of the portfolio an analyst exposes the portfolio to actual historical returns over a fixed number of days. After the position is exposed to the past risk factors, portfolio values are ranked from smallest to largest. The portfolio value that represents the

[5]Note that non-parametric VaR is not to be confused with non-parametric statistical procedures.

designated risk tolerance level becomes the VaR estimate; for instance, the 5% quantile of the distribution for the 95% level of confidence.[6]

The historical simulation method has been praised for its flexibility and ease of implementation. There is no reliance on distributional assumptions, therefore deviations from normality are not a problem (Mahoney; Linsmeier and Pearson, 1996). When there are options positions in the portfolio, the historical simulation method captures the non-linearity of the position. Historical estimation is free of risks due to parameter estimation, and correlation effects between various assets are modeled implicitly since profits are in essence paired against losses for the entire position (Linsmeier and Pearson, 1996). Finally, historical simulation is easy to understand by management, one of the prime considerations in using VaR estimates (Mahoney; Linsmeier and Pearson, 1996; JP Morgan *Risk Metrics*). To improve the performance of the historical simulation method, however, Butler and Schachter propose a Kernel estimation procedure which provides a standard error of the estimated quantile that represents the Value-at-Risk.

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; Hendricks). 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). 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 placed 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.

Monte Carlo simulation generates pseudo-random values of the risk factors of the portfolio based on a predetermined data generating process. 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 (personal communication), greatly criticize Monte Carlo methodology for estimating VaR since it is very prone to specification error, especially with complex portfolios. The underlying data generating process must also be determined. Jorion (1997) suggests using geometric Brownian motion to describe the underlying data generating process. Time variation may be added through GARCH variance terms (see Jorion, 1997 pg. 238 for details); however, time variation may be distorted with Monte Carlo methods, suggesting a trade-off between time

[6]See Linsmeier and Pearson (1996, 1997) for an excellent example of the historical simulation method.

variation and model flexibility. Ho, Chen, and Eng 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 (Ho, Chen, and Eng). Also, management may find it difficult to understand Monte Carlo simulation methods (Linsmeier and Pearson, 1996).

As an alternative to pure Monte Carlo methods, Jorion (1997), Sortino and Forsey, and Duffie and Pan 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.

Empirical Evaluation of Alternative Value-at-Risk Models

The previous section outlined the pro's and con's of various VaR estimation methods. There is, however, a growing literature that empirically examines 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 JP Morgan *Risk Metrics* 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 tested the out-of-sample performance of the alternative VaR estimates. Mahoney found that VaR estimates computed with the historical simulation method were more representative of actual portfolio losses than that of either the two parametric methods 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 found that they were biased for high levels of confidence (>99%) in that they "understated the frequency of large downward movements in portfolio values" (Mahoney, p. 214). This bias was more severe with the equity portfolios than with the exchange rate portfolios, 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%).[7]

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[7]The parametric VaR estimates for the equity positions were overly biased due to the weight placed on the stock market crash of 1987, especially for the equally weighted model. When 1987 was removed from the sample, the VaR estimates were unbiased (Mahoney).

Using similar data and methods to that of Mahoney, Hendricks compared several parametric and full-valuation methods of VaR for random exchange rate portfolios. For the parametric methods, Hendricks 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 concluded generally that all VaR estimates measured the risk that they were intended to cover, in particular at the 95% level. Hendricks did note that the JP Morgan *Risk Metrics* 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, 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, 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 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 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" (Hendricks, p. 56).

In response to observed leptokurtosis in several financial return series, Venkataraman suggested and tested the use of a mixture of normals technique utilizing a quasi-Bayesian maximum likelihood procedure (QB-MLE) to account for the leptokurtosis often identified with financial time series. Modeling several currency positions, Venkataraman found that the mixtures of normals approach performed better than models that assumed normality for both individual currency positions and for a random portfolio of currencies. However, Venkataraman did not test the QB-MLE procedure against commonly used VaR estimators such as the exponential moving average technique advocated by JP Morgan *Risk Metrics* 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, et al. 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" (Green, et al., 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; Hendricks). Despite the ability of robust estimates to reduce the effects of leptokurtosis, Green, et al. were critical of robust techniques since they tended to underestimate actual risks, thus creating a new bias in the estimates.

Beder compared alternative full-valuation procedures of calculating VaR for portfolios of Treasury strips and equity index positions. Contrary to Mahoney and Hendricks, Beder 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. The differences among models was even greater when non-linear positions were included in the portfolio. Beder was adamant in the view that risk measurement using VaR is not a panacea for good risk management practices. However, Beder failed to test the various estimates out-of-sample 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 or of a particular procedure.

The study of Jackson, et al. was unique in that it examined real portfolios held by a bank in contrast to single asset or a randomly selected portfolios of assets such as the studies of Mahoney, Hendricks and Beder. "Studies that analyze VaR modeling on the basis of, for example, a single equity index or FX rate seem to us to be ill-advised, therefore, it is important to look at realistic portfolios" (Jackson, et al., p. 87). The portfolios they examined were for foreign equity and exchange rate positions. Similar to the studies of Mahoney and Hendricks, they examined the simple historical simulation approach (full-valuation), as well as the equally weighted and an exponentially weighted moving average approaches (parametric). Despite the superior forecast performance of the parametric models, they found that the historical simulation method better represented the tail probabilities, especially at the 99% level of confidence, consistent with the results of Mahoney and Hendricks.[8] 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, they found their parametric models better explained time varying volatility and provided 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 examined how sensitive VaR estimates were across model builders (vendors) for the same estimation technique. Marshall and Siegel coined the potential variation among model builders using the same estimation technique as *implementation risk.* Similar to Jackson, et al., they concluded that implementation risk may differ among asset classes examined, thus reenforcing 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 FX forwards. They noted that for non-linear positions (FX options) wide variations existed among the vendors for VaR estimates when using the *Risk Metrics* methodology (delta+gamma approximation). When using non-parametric (full-valuation) for FX options positions, they found a wide variation among the alternative non-parametric procedures used by vendors.

[8]Jackson et al. defined tail probabilities as the percent of losses that exceeded the Value-at-Risk estimate. For instance, did losses exceed the 1% cutoff more than 1% of the time?

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., the 95% level). Full-valuation methods model extreme tail behavior (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 Value-at-Risk are the ease of use, flexibility, cost of implementation, and degree to which management and investors find the risk measure useful. Literature related to Value-at-Risk is continually growing as researchers attempt to reconcile several of the issues presented in this review.

VAR IN AGRICULTURAL ECONOMICS

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; Garcia, et al.; Fackler and McNew) and the cattle feeding margin (Peterson and Leuthold). These situations provide realistic portfolios for examining the performance of alternative Value-at-Risk 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 Value-at-Risk. The performance of VaR techniques when applied to agricultural product 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, have been applied to agricultural prices (Yang and Brorsen, 1992, 1993; Garcia, et al.; Kroner, et al.). The exponentially weighted moving average technique advocated by JP Morgan's *Risk Metrics* may provide a useful alternative to Multivariate GARCH procedures for developing time varying variance/covariance matrices for agricultural risk management purposes. The emphasis that VaR places on measuring tail behavior provides added motivation for testing common volatility estimating procedures 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 allows implied volatility estimates to be employed as VaR estimates. The use of implied volatility estimates in developing VaR measures has been suggested by researchers and practitioners as being superior to other methods since implied volatility is the markets' 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 Value-at-Risk. This issue calls into question the performance of different volatility forecasting procedures to calculate VaR at horizons longer than one day.

Despite 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, Value-at-Risk 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 managers and growers estimates of downside risk in accordance with positions held in Hedge-to-Arrive agreements. VaR also has potential uses 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 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 to 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 correlations. Despite the recent attention and popularity of Value-at-Risk, the risk measure should only be viewed as another measure in the risk manager’s toolkit and not a substitute for prudent risk management practices.

REFERENCES

Beder, T.S. (1995), “VaR: Seductive but Dangerous,” *Financial Analysts Journal*, September-October 1995, pp. 12-24.

Bollerslev, T., Chou, R.Y., and Kroner, K.F. (1992): “ARCH Modeling in Finance: A Review of the Theory and Empirical Evidence,” *Journal of Econometrics*, 52: 5-59.

Boudoukh, J., Richardson, M., and Whitelaw, R.F. (1997): “Investigation of a Class of Volatility Estimators,” *The Journal of Derivatives*, 4: 63-71.

Butler, J. S. and Schachter, B. (1997): "Estimating Value-at-Risk With a Precision Measure By Combining Kernel Estimation with Historical Simulation," forthcoming, *Review of Derivatives Research.*

Christofferson, P.F. and Diebold, F.X. (1997): "How Relevant is Volatility Forecasting for Financial Risk Management," Working Paper, The Wharton School, University of Pennsylvania.

Diebold, F.X., Hickman, A., Inoue, A., and Schuermann, T. (1997): "Converting 1-Day Volatility to h-Day Volatility: Scaling by $\sqrt{h}$ is Worse than You Think," Working Paper, The Wharton School, University of Pennsylvania.

Duffie D., and Pan, J. (1997): "An Overview of Value at Risk," *The Journal of Derivatives*, 4: 7-49.

Fackler, P.L., and McNew, K.P. (1993): "Multiproduct Hedging: Theory, Estimation, and an Application," *Review of Agricultural Economics*, 15: 521-535.

Figlewski, S. (1997): "Forecasting Volatility," *Financial Markets, Institutions, and Instruments*, 6: 2-87.

Fuhrman, R. (1997): "Stress Testing Portfolios to Measure the Risk Faced by Futures Clearinghouses," Proceedings of the NCR-134 Conference on Applied Commodity Forecasting and Risk Management, pp. 401-411.

Garcia, P., Roh, J.S., and Leuthold, R.M. (1995): "Simultaneously Determined, Time Varying Hedge Ratios in the Soybean Complex," *Applied Economics,* 27: 1127-1134.

Green, H.G., Martin, R.D., and Pearson, M.A. (1996): "Robust Estimation Analytics for Financial Risk Management," IEEE/IAFE Conference on Computational Intelligence for Financial Engineering (CIFEr), pp. 190-198.

Hendricks, D. (1996): "Evaluation of Value-at-Risk Models Using Historical Data," *Federal Reserve Bank of New York Economic Policy Review,* April. pp. 39-69.

Ho, T.S.Y, Chen, M.Z.H, and Eng, F.H.T. (1996): "VAR Analytics: Portfolio Structure, Key Rate Convexities, and VAR Betas," *The Journal of Portfolio Management*, 23: 90-98.

Hopper, G.P. (1996): "Value-at-Risk: A New Methodology for Measuring Portfolio Risk," *Business Review Federal Reserve Bank of Philadelphia*, July/August, pp. 19-31.

Jackson, P., Maude, D.J, and Perraudin, W. (1997): "Bank Capital and Value at Risk", *The Journal of Derivatives,* 4: 73-89.

Jorion, P. (1997): Value at Risk: The New Benchmark for Controlling Derivatives Risk, Irwin Publishing, Chicago, IL.

Jorion, P. (1996). "Risk^2: Measuring the Risk in Value at Risk," *Financial Analysts Journal*, November-December, pp. 47-56.

J.P. Morgan *Risk Metrics™* (1995, 1996, 1997): Technical Document, 4th Edition, Morgan Guaranty Trust Company, New York., various pages, **http://www.jpmorgan.com/RiskManagement/RiskMetrics/pubs.html**

Kroner, K.F, Kneafsey, K.P., and Claessens, S. (1994): "Forecasting Volatility in Commodity Markets," *Journal of Forecasting*, 14: 77-95.

Linsmeier, T.J. and Pearson, N.D. (1997): "Quantitative Disclosures of Market Risk in the SEC Release," *Accounting Horizons*, 11: 107-135.

Linsmeier, T.J. and Pearson, N.D. (1996): "Risk Measurement: An Introduction to Value at Risk," Office for Futures and Options Research Working Paper #96-04, 44 pp.

Mahoney, J. M. (1995 or 1996): "Empirical-based versus Model-based Approaches to Value-at-Risk: An Examination of Foreign Exchange and Global Equity Portfolios," Federal Reserve Bank of New York, Unpublished Manuscript.

Marshall, C., and Siegel, M. (1997): "Value at Risk: Implementing a Risk Measurement Standard," *The Journal of Derivatives*, 4: 91-111.

Peterson, P.E., and Leuthold, R.M. (1987): "A Portfolio Approach to Optimal Hedging for a Commercial Cattle Feedlot," *The Journal of Futures Markets*, 7: 443-457.

Sortino, F.A. and Forsey, H.J. (1996): "On the Use and Misuse of Downside Risk," *The Journal of Portfolio Management*, Winter 1996, pp. 35-42.

Tzang, D.N., and Leuthold, R.M. (1990): "Hedge Ratios Under Inherent Risk Reduction in a Commodity Complex," *The Journal of Futures Markets*, 10: 497-504.

Venkataraman, S. (1997): "Value at Risk for a Mixture of Normal Distributions: The Use of Quasi-Bayesian Estimation Techniques," *Economic Perspectives: A Review from the Federal Reserve Bank of Chicago*, 21: 2-13.

Yang, S.R. and Brorsen, B.W. (1993): "Nonlinear Dynamics of Daily Futures Prices: Conditional Heteroskedasticity or Chaos?" *The Journal of Futures Markets*, 13: 175-191.

Yang, S.R., and Brorsen, B.W. (1992): "Nonlinear Dynamics of Daily Cash Prices," *American Journal of Agricultural Economics*, 74: 707-715.