A Comparison of Criteria for Evaluating Risk Management Strategies

ABSTRACT: Several criteria that produce rankings of risk management alternatives are evaluated. The criteria considered are Value at Risk, the Sharpe ratio, the necessary condition for first degree stochastic dominance with a risk free asset, and the necessary condition for second degree stochastic dominance with a risk free asset. The effectiveness of the criteria increases as decision-makers are assumed to be more risk averse and have greater access to financial leverage.

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Recently there have been significant advances in the ability to develop probabilistic forecasts of the returns to risky investments. Personal computer simulation packages such as @RISK and AgRisk enable decision-makers to quickly develop approximations to the cumulative distribution of returns associated with an investment. Agricultural risk management education has begun to provide producers with probabilistic information about the risks that they face. Examples of these educational efforts are the AgRisk computer program (http://www-agecon.ag.ohio-state.edu/agrisk/), the Center for Agricultural and Rural Development's interactive LDP database (http://cardsrv6.card.iastate.edu/LDPStart.htm), probabilistic grain price forecasts on Michigan State's web site (http://www.msu.edu/user/hilker/), and other producer education efforts (Baker and Patrick, Iowa State).

Analyzing probabilistic information can be a challenging activity for managers. Unless the decision-maker is able to completely specify his/her utility function it is not possible to implement the expected utility hypothesis. As a result, risk efficiency criteria such as stochastic dominance or mean-variance analysis can be used to identify sets of projects deserving further managerial consideration. While these methods are useful, they often leave the decision-maker with many alternatives. Likewise, simulation packages developed to aid producer risk management strategy selection do not explicitly calculate these efficient sets. Instead, they often present the decision-maker with descriptive information such as the means, standard deviations, and values at risk (see AgRisk as an example).

Many criteria are available to summarize and rank the desirability of various risk management strategies. The optimality of decisions based upon these rankings is reliant upon a criterion's ability to concisely summarize information about the risks and returns of particular strategies. This paper compares the rankings produced by several ranking criteria including two ranking criteria that are new to the literature. The rankings produced by these criteria are examined to identify important differences and consistencies across the criteria. The criteria are described and related to expected utility maximization in the next section. Then the data and the correlation of the rankings produced by each of the criteria are presented. Finally, the results are discussed and conclusions about the usefulness of the various criteria are offered.

The Ranking Criteria

Ranking criteria are intended to assist a decision-maker in choosing among mutually exclusive investment alternatives on which they have probabilistic information regarding the returns associated with each alternative. The criteria considered in this paper all have some basis in expected utility maximization although some are more closely related to the concept than others. Two of the criteria, value at risk (VAR) and the Sharpe ratio, have been widely used by the financial community to evaluate the risks associated with investments and to evaluate the returns associated with investments.

Value at Risk

Manfredo and Leuthold review some of the current uses of VAR and suggest that it may have application in agricultural risk management. VAR considers a probability level in the cumulative distribution function (CDF) and finds the associated quantile or money outcome from the *X* axis in a standard graph of the cumulative distribution[1]. For this study VAR is defined by equation (1).

(1) $$VAR_{Xp} = Q_X(p)$$

where VAR_{Xp} is the value at risk under alternative X and cumulative probability level p, $Q_X(p)$ is the quantile function of activity X evaluated at cumulative probability level p.

The quantile function of activity X is defined as the inverse of the cumulative distribution function associated with the returns to activity X in (2).

(2) $$Q_X(p) = F_X(z)^{-1}$$

where $F_X(z)$ is the cumulative distribution function associated with the returns to activity X which is defined in equation (3), and z is a monetary return level.

(3) $$F_X(z) = \Pr(x \leq z)$$

where Pr returns the probability that the monetary returns (x) to activity X are less than or equal to some level z.

For a given level of probability, a larger VAR_{Xp} is preferred by all decision-makers who prefer more wealth to less. Thus, the VAR_{Xp} criterion can be used to rank projects by choosing a specific probability level in the CDF and ordering projects according the magnitude of their associated quantiles or VAR_{Xp}.

VAR_{Xp} is clearly related to first order stochastic dominance (FSD). For instance, if VAR_{Xp} is greater than or equal to VAR_{Yp} for all values of cumulative probability, then strategy X would dominate strategy Y by FSD. When all strategies are evaluated at a single probability level, the strategy with the largest VAR_{Xp} is guaranteed to be a member of the FSD set. However, the strategy with the largest VAR_{Xp} need not be a member of the second degree stochastic dominance (SSD) set[2]. More importantly, when used as a ranking criterion, VAR focuses on a particular probability level. In most agricultural risk management situations, there is not a clear economic justification for selecting the probability level at which VAR_{Xp} is evaluated. A more intuitive objective is to evaluate strategies with respect to the likelihood that they will or will not produce some benchmark return level.

Benchmark Returns, the Risk Free Return, and Investment Analysis

The concept of a benchmark return is important in risk management analysis. The risk free return is an important benchmark for two key reasons. First, it allows one to incorporate the idea of an opportunity cost into investment analysis. Second, its inclusion can produce a theoretical separation of the investment decision from risk preferences. For example, when agents are allowed to borrow and lend at the risk free rate of return in Markowitz's mean-variance framework, the efficient set is reduced to one expected utility maximizing investment (Tobin, Sharpe). An investment ranking criterion known as the Sharpe ratio is a result of this analysis.

The Sharpe Ratio

Sharpe (1966, 1975, 1994) showed that the Sharpe ratio could be used to completely characterize choice among mutually exclusive investments when borrowing and lending were possible. Following Sharpe (1994), denote the difference in returns between asset *i* and the risk free asset as (4).

(4) $$\tilde{D}_i = \tilde{R}_i - R_f \qquad \forall i = 1,2,\ldots n$$

where $\tilde{D}_i$ is a random variable representing the difference between the random return to asset *i*, $\tilde{R}_i$, and the fixed return to the risk free asset, R_f. When there are *t* states of nature, the expected return differential for asset *i*, m_i, is given by (5) and the standard deviation of the return differential for asset *i*, s_i, is given by (6).

$$(5) \qquad m_i = \frac{\sum_{j=1}^{t} \tilde{D}_{ij}}{t} \qquad \forall i = 1,2,\ldots n$$

$$(6) \qquad s_i = \sqrt{\frac{\sum_{j=1}^{t} \left(\tilde{D}_{ij} - m_i\right)^2}{t-1}} \qquad \forall i = 1,2,\ldots n$$

The Sharpe ratio for asset *i* is given by (7).

$$(7) \qquad S_i = \frac{m_i}{s_i}.$$

Given a set of mutually exclusive investment alternatives that differ only by their first two moments, all expected utility maximizing decision makers with the ability to borrow or lend will invest in the alternative with the largest Sharpe ratio (Sharpe, 1994).

The Sharpe ratio is similar to the coefficient of variation, with the important difference that the return to the risk free asset has been subtracted from the returns to the risky asset (Sharpe, 1994). The measure has intuitive appeal as Sharpe (1994) shows that it is related to the t-statistic used to determine the probability that there is no difference between the returns to the risky asset and the returns to the risk free asset.

These characteristics make the Sharpe ratio quite powerful. It considers the economic concept of the opportunity cost of borrowing and lending, and under certain circumstances is completely consistent with expected utility maximization. However, the mean-variance model that generates the Sharpe ratio relies upon several seemingly strong assumptions. The most obviously violated assumption is the requirement that the distributions being compared differ only by their first two moments. One purpose of using risk management alternatives such as options is to modify the skewness of the return distribution.

While the assumptions used to justify the theoretical separation in the mean-variance model rarely hold in most agricultural risk management contexts, the inclusion of a risk free alternative in the ordinary stochastic dominance (SD) framework produces what Levy and Kroll (1979) call an empirical separation. The implication of this empirical separation is that when the risk free alternative is included in the analysis, all but a small number of alternatives are typically inefficient in a SD sense. Because the SD criteria are not dependent upon restrictive distributional assumptions, it is possible that a ranking criteria based upon the stochastic dominance with a risk free asset (SDRA) criteria could produce rankings that are theoretically consistent with a wide variety of expected utility maximization.

Necessary Condition for First Degree SDRA

The SDRA criteria developed by Levy and Kroll (1978) and Levy (1998) incorporate the concept of financial leverage into the ordinary SD framework. The first degree SDRA efficient set is a subset of the FSD efficient set and contains the expected utility maximizing strategy for all decision makers who have access to borrowing and lending at the risk free return and prefer more wealth to less.

The necessary condition for first degree SDRA provides a simple ranking criterion that has intuitive appeal. The criterion is shown given by (8).

(8) $$Nfsdra_X = F_X\left(r\right)$$

where $Nfsdra_X$ is the probability returned when the cumulative distribution of activity X, $F_X(\cdot)$, *is* evaluated at the risk free return, r. The strategy with the smallest value of *Nfsdra* is preferred.

This criterion is similar to the VAR_{Xp} criterion. However, unlike VAR_{Xp} there is an economic rational for choosing the evaluation point. The risk free return provides an opportunity cost with which to evaluate investments. The most desirable strategy under this criterion is the strategy that has the smallest probability of failing to generate the risk free return. Further, the investment with the lowest cumulative probability at the risk free return could potentially dominate all other activities by first degree SDRA, insuring that the strategy with the smallest *Nfsdra* must be a member of the first degree SDRA set. However, the top ranked strategy under this criterion is not required to be a member of the SSD or second degree SDRA efficient sets.

The *Nfsdra* criterion measures risk in only a limited FSD sense. While the first degree SDRA efficient set is typically smaller than the FSD efficient set, the empirical separation is not ordinarily achieved with only first degree SDRA. Thus, one would suspect that the strategy with the smallest value of *Nfsdra* would not typically be an EU maximizing choice for a wide range of risk averters. The second degree SDRA risk efficiency criterion typically produces a much smaller set than the first degree SDRA criterion. Likewise, the criterion based on the necessary condition for second degree SDRA is the only criterion capable of assuring that the most desirable strategy will be a member of both the ordinary SSD and second degree SDRA efficient sets.

<u>The Necessary Condition for Second Degree SDRA</u>

For investment X to dominate investment Y by second degree SDRA it is necessary that the value of p that solves (9) is smaller under investment X than under investment Y (Levy and Kroll, Levy).

$$Nssdra_X = p \quad \text{that solves}$$

(9) $$rp = \int_0^p Q_X(t)dt$$

where $Nssdra_X$ is the cumulative probability level p, r is the risk free return, and $Q_X(t)$ is the quantile function for investment X. The investment with the smallest *Nssdra* value could potentially dominate all other strategies by second degree SDRA and is therefore a member of both the SSD and second degree SDRA efficient sets.

Figure 1 provides a graphical interpretation of the *Nssdra* condition. The figure shows a CDF, $F(x)$, with probability on the vertical axis and returns on the horizontal axis. For simplicity, $F(x)$ is drawn as a straight line, which passes through the origin. The risk free return is assumed to be 10. The left side of (9) represents the area of a rectangle with length r and height p. The integration on the right side of (9) is of the quantile function so the area represented is above $F(x)$ and below p. In order for (9) to hold one must equate these areas. Because the area to the left of r, above $F(x)$, and up to p are common to both sides of (9), one can see that when the area in a is equal to the area in b the condition will hold. In Figure 1 this is defined by the horizontal intercept of $F(x)$ occurring at 0, $F(r)$ being equal to 0.25 and p equal to 0.5. As long as the expected value of X is greater than the risk free return and $F(x)$ does not lie entirely to the right of r, the value of p that solves (9) will always be a probability less than one (Levy and Kroll, 1978).

The *Nssdra* measure can be interpreted as the minimum amount of cumulative probability needed to rule out ordinary SSD of the cumulative distribution of the risk free asset over the cumulative distribution of the risky asset. The *Nssdra* measure is similar to a safety first measure because it measures the area below the CDF to the left of the risk free rate. However, it also considers the rate at which the CDF pulls away from the CDF associated with the risk free return. Given the same area below the CDF and to the left of the risk free rate, the *Nssdra* measure penalizes distributions that move away from the risk free rate slowly.

Theoretically, the *Nssdra* condition is attractive because the second degree SDRA efficient sets tend to be small (Levy and Kroll, 1979). Thus, unlike the guarantee of membership in the FSD set, the guarantee of membership in the second degree SDRA efficient set means that the strategy is one of a few potential expected utility maximizing strategies. The *Nssdra* criterion is likely to be more consistent with EU maximization than the other ranking criteria because it takes into account a wider range of the CDF. At the same time, it is not dependent upon the distributional assumptions of the Sharpe ratio. The unattractive feature of this condition is that it is computationally more intensive than the other criteria.

Certainty Equivalents

The ranking criteria discussed up to this point are not necessarily consistent with expected utility maximization. The certainty equivalents produced by the power utility function allow for a complete ranking of risky projects that are consistent with specific cases of expected utility maximization. To compute the certainty equivalent (CE) rankings, the coefficient of relative risk aversion, r, was set to four different levels. These levels might correspond to classes of decision makers who could be considered slightly risk averse, $r = 0.5$, moderately risk averse, $r = 1$ and 1.5, and highly risk averse, $r = 4$.

The rankings produced by the Sharpe ratio, *Nfsdra*, and *Nssdra* criteria are all influenced by the assumption that a decision maker can use financial leverage to adjust the amount of total risk associated with a particular risk management project. The certainty equivalent rankings were calculated based upon expected utility maximization in which the level of financial leverage was a variable. That is, expected utility was maximized for the following problem:

$$(10) \qquad \max_{\substack{a_j \\ j=1,2,\ldots n}} EU_j = \sum_i \frac{p_{ij}\left[\left(1-a_j\right)r + aX_{ij}\right]^{(1-r)}}{(1-r)}$$

where a_j is the amount of financial leverage which maximizes expected utility for strategy *j* and is constrained to be non-negative, EU_j is expected utility of strategy *j*, p_{ij} is the probability of state of nature *i* occurring under strategy *j*, *r* is the risk free return, X_{ij} is the monetary return to strategy *j* when state *i* occurs, and r is the coefficient of relative risk aversion. This problem was solved for 4 different values of r, and with 4 different upper bounds on a. By varying the upper bound on a one can assess the effect of different assumptions about the amount of financial leverage that the decision maker has access to. The upper bounds on a were set to values of 1, 2, 3, and 4. These upper bounds correspond to project debt to equity ratios of 0, 1, 2, and 3. In particular, the upper bound of 1 corresponds to cases where the decision maker can only lend at the risk free rate. Because the optimal level of leverage fell on the upper bound of each range of leverage for all levels of risk aversion except $\rho = 4$, the certainty equivalents increased as leverage increased.

Data

The gross revenue distributions associated with two case farms were compared with the ranking criteria. Specifically, the AgRisk simulation model was used to generate gross revenue distributions for 13 pre-harvest risk management strategies for a 300 acre corn and soybean farm in Decatur county Indiana. The risk free return was calculated based upon the cash rental rate plus variable costs of operation for a 300 acre Indiana farm with average quality soils given in Doster, et al. The return distributions produced by Nydene's simulation of a 1,000 acre crop farm and 175 sow farrow to finish hog farm under various risk management policies were also compared with the rules. Nydene's study considered 23 risk management strategies designed to manage both output price and output quantity risk. The risk free return for this farm was based upon a 9 percent borrowing rate and an estimate of the total assets of the simulated farm. The strategy codes used to report the results of both models are explained in Table 1.

The means, standard deviations, and standardized skewness measures for the 13 pre-harvest risk management strategies simulated with AgRisk are shown in Table 2. Table 3 contains the same information for the 23 risk management strategies simulated by Nydene. In both models, the natural hedge or cash sale strategy produced the largest expected return. In the AgRisk simulations this strategy also had the largest standard deviation. The smallest standard deviation in the AgRisk simulation was produced by the forward contract 66 percent of expected production strategy (Fwd 66%). The strategies have different levels of skewness in both sets of distributions. The ordinary SSD and second degree SDRA efficient sets contained 6 and 4 strategies in the AgRisk simulation and 6 and 3 strategies in the crop and hog farm model. The strategies in each of these sets are indicated with the ‡ (SSD efficient) and * (second degree SDRA efficient) symbols.

The VAR_{Xp}, Sharpe ratio, *Nfsdra*, and *Nssdra* criteria were used to rank the desirability of the strategies for each model. Within each set of results the most desirable strategy was assigned a ranking of 1, the next most desirable a ranking of 2, and so on. In the AgRisk case, three strategies were identified as the most desirable alternatives. The *Nfsdra*, *Nssdra*, and all but one CE ranking identified the Fwd 33% strategy as the most desirable strategy. The Sharpe ratio and

VAR_{10} rankings identified the Fwd 66% strategy as the preferred strategy and Fwd 33% as the second best strategy. The slightly risk averse decision maker (r = 0.5) who was only allowed to lend at the risk free return ($a \in [0,1]$) preferred the natural hedge strategy. All three of the top rated strategies were members of the SSD efficient set, while only Fwd 33% was a member of the second degree SDRA set. Thus, although the top ranked strategy under the VAR_{10}, Sharpe ratio, and *Nfsdra* criteria is not required to be a member of the SSD set, all identified a SSD member.

In the crop and hog farm simulation the VAR_{10} and all but one CE ranking identified hedge hogs (HH) as the most desirable strategy. This strategy was rated as the second most desirable by the Sharpe ratio, *Nfsdra*, and *Nssdra* criteria. The *Nfsdra*, *Nssdra*, and CE ranking with r = 4 and $a \in [0,4]$ identified the practice of buying actual production history crop insurance, hedging crops, hedging hogs, and hedging feed (APH HC HH HF) as the most desirable strategy. Both of the HH and APH HC HH HF were members of both the SSD and second degree SDRA efficient sets.

In general, the criteria performed relatively well in that they identified strategies that were rated highly under specific cases of expected utility maximization. All criteria also identified a member of the SSD set as the preferred strategy. To explore the correspondence of the rankings more thoroughly the rankings were analyzed with a correlation analysis.

<u>Correlation of the Rankings</u>

The correlation of the rankings shows a more sophisticated relationship between the rankings of the criteria. It also allows one to assess the correspondence of the rankings to the assumptions about borrowing and risk aversion. Table 4 shows the correlation matrix of the rankings produced by the Sharpe ratio, VAR_{10}, *Nfsdra*, *Nssdra* criteria and the CE criteria with the widest leverage bounds for the AgRisk simulation. The rankings produced by the Sharpe ratio were more highly correlated with the non-CE rankings than any of the CE rankings. As the level of relative risk aversion increased, the Sharpe ratio rankings tended to be more highly correlated with the CE rankings. When the level of relative risk aversion was low, the correlation was relatively low (0.47).

The VAR_{10} rankings were highly correlated with the *Nfsdra* rankings, indicating that the 10 percent level in the CDF tended to correspond to the risk free return for most strategies. As with the Sharpe ratio, the correlation between the VAR_{10} rankings and the CE rankings increased as the level of relative risk aversion increased. This is consistent with the increasing dis-utility associated with low return states of nature as risk aversion increases.

The *Nssdra* rankings were highly correlated with the VAR_{10} and *Nfsdra* rankings. As the level of relative risk aversion increased, the correlation between the *Nssdra* and CE rankings increased. When relative risk aversion was high, the *Nssdra* rankings were nearly perfectly correlated with the CE rankings. Of the non-CE criteria, the *Nssdra* rankings were the most highly correlated with the CE rankings for every level of relative risk aversion. The correlation between the various CE rankings show that in the AgRisk case the rankings are relatively highly correlated across levels of relative risk aversion.

Table 5 shows the correlation between the rankings produced by the non-CE criteria and the CE rankings for all levels of borrowing. As expected, the correlation between the Sharpe ratio, *Nfsdra*, and *Nssdra* criteria generally increased as the bounds of leverage are widened. Again, the *Nssdra* rankings were the most highly correlated with the CE rankings for all levels of leverage and risk aversion. The correlation between the Sharpe ratio and the CE rankings improved as the bounds of leverage increased until the coefficient of relative risk aversion reached 4. The highest correlation achieved by the Sharpe ratio was 0.77, which indicates that the optimality of the Sharpe ratio is quite dependent upon the return distributions only differing by the first two moments. The *Nssdra* condition was the most consistent for all levels of leverage even those when only lending was allowed ($\alpha = 0 – 1$). In all cases, the correlation between the *Nssdra* and CE rankings was greater than 0.6. For values of relative risk aversion above 1.5 the correlation was no lower than 0.74. In the highly risk averse case the CE and Nssdra rankings were nearly perfectly correlated.

The correlation of the rankings for the crop and hog farm simulation model are presented in Table 6. These results show the correlations among the Sharpe ratio, VAR_{10}, *Nfsdra*, and *Nssdra* rankings to be higher than in the AgRisk case. For the crop and hog farm simulation, all non-CE rankings possess low correlation with the CE rankings under the slightly risk averse case. Unlike the AgRisk case, the *Nssdra* rankings are not the most highly correlated with the CE rankings until the level of relative risk aversion reaches the most risk averse case. However, at this level the correlation is very high, 0.96. Again, the level of correlation between the non-CE criteria rankings and the CE rankings increases as risk aversion increases. For this simulation, the correlations increase relatively quickly as relative risk aversion increases. When relative risk aversion reaches 1.5, the correlation of all non-CE rankings is at least 0.90. When risk aversion is high, the *Nfsdra* and *Nssdra* rankings are very highly correlated with the CE rankings. The low level of correlation among the various CE rankings indicates that the desirability of many projects changes considerably as risk aversion changes. For this reason, it is not surprising that the non-CE rankings are not highly correlated with the CE criteria for all levels of risk aversion.

The correlation between the non-CE rankings and the CE rankings with different leverage bounds for the crop and hog simulation are shown in Table 7. The results again show that as the bounds of leverage widen, the correlation levels typically increase. When the bounds of leverage are wide ($a \in [0,4]$) and the level of risk aversion is high (r= 4) the rankings produced by all of the non-CE criteria are nearly perfectly correlated with the CE criteria. The results show that as the bounds of leverage widen, the correlation between the non-CE rankings and all CE rankings except those with r = 4 increases.

Conclusions

The ranking criteria considered in this paper use simplified measures of risk and return to rank alternative risk management strategies. In some cases the measure was as simple as evaluating one point on a cumulative distribution function. The criteria performed relatively well in that they all selected strategies that were at least members of the SSD efficient set. This is in spite of the fact that only the *Nssdra* criterion is guaranteed to do so.

Criteria like VAR_{Xp}, *Nfsdra*, and *Nssdra* focus on a region of the cumulative distribution function. The *Nssdra* criterion covers the largest area and is therefore the most consistent with EU maximization. The Sharpe ratio’s dependence upon the assumption of differences in the strategies being compared being confined to the first two moments appears to cause its rankings to diverge from the CE rankings. When agents are not very risk averse, none of the rankings were highly correlated with the CE rankings. However, in general, the top ranked strategy was usually consistent with the strategy that had the largest CE. This indicates that the preference for the top strategy did not change considerably although the rankings of the other projects did change.

In all cases rankings produced by the criteria correspond more closely to CE rankings produced with higher levels of relative risk aversion than those produced with low levels of relative risk aversion. Likewise, the correlation between the CE and non-CE rankings increased as the amount of leverage the decision maker had access to increased. When the level of relative risk aversion is high and the bounds of leverage wide, the *Nssdra* rankings were nearly perfectly correlated with the CE rankings.

The ability to approximate the cumulative distribution function of returns to risk management strategies has the ability to improve risk management decision making. Decision makers seeking measures to summarize the risk and return of various risk management strategies can easily apply the criteria presented in this paper. The results of the paper indicate that rankings produced by these criteria tend to identify solutions that are at least potentially expected utility maximizing for risk averse agents (members of the SSD efficient set). However, the results suggest against using such simplified criteria when agents are not very risk averse. Likewise, when borrowing is not allowed, the criteria have less correspondence to the expected utility maximization. When using the criteria it is most reasonable to use the *Nssdra* criterion. The highest ranked strategy under this criterion is guaranteed to be a member of the typically small second degree SDRA efficient set which contains all of the potential expected utility maximizing strategies for risk averse agents with access to financial leverage.

1. In many financial studies value at risk implies estimation of the return distribution as well.

2. If VAR is evaluated at the smallest value of probability occurring among a group of investments then the strategy with the largest VAR would be a member of the SSD set.

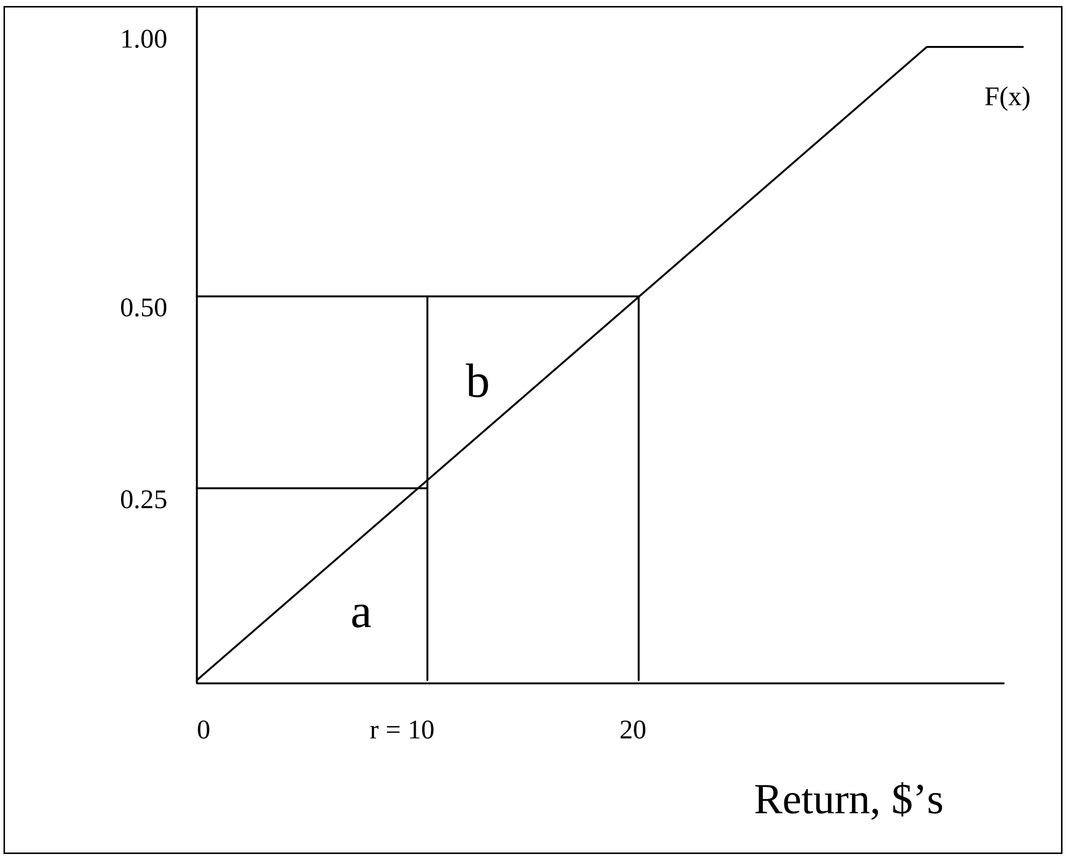

Figure 1. The *Nssdra* criterion.

Table 1. Strategy Codes for Crop/Hog Farm Simulation Model.

Code	Description of Strategy
	AgRisk Simulation
Natural Hedge	Cash sale at harvest
Fwd	Forward contract 33, 66, or 100 percent of expected production
Hedge	Forward contract 33, 66, or 100 percent of expected production
ATM PUT	Buy at the money puts on 33, 66, or 100 percent of expected production
PUT-CALL	Buy out of the money puts and sell out of the money calls on 33, 66, or 100 percent of expected production
	Crop and Hog Farm Simulation*
APH	Buy Actual Production History Insurance
CO	Buy Crop Options
CRC	Buy Crop Revenue Coverage Insurance
GRP	Buy Group Risk Plan Insurance
HC	Hedge Crops
HF	Hedge Feed
HH	Hedge Hogs
HO	Buy Hog Options
Naïve	Cash Sale

Source: Table 4.1 Nydene (1999).

Table 2. The Means and Standard Deviations for the Marketing Strategies Simulated with AgRisk.

Strategy	Mean	Standard Deviation	Standardized Skewness*
‡Natural Hedge	$ 87,147	$ 14,317	0.65
Fwd 100%	$ 86,525	$ 13,330	-0.79
‡Fwd 66%	$ 86,987	$ 11,760	0.02
‡*Fwd 33%	$ 87,075	$ 12,298	0.56
Hedge 100%	$ 86,069	$ 13,314	-0.59
Hedge 66%	$ 86,436	$ 11,976	0.04
‡*Hedge 33%	$ 86,792	$ 12,377	0.53
‡*ATM PUTS 100%	$ 86,769	$ 12,384	0.58
‡*ATM PUTS 66%	$ 86,897	$ 12,734	0.71
ATM PUTS 33%	$ 87,022	$ 13,390	0.73
PUT-CALL 100%	$ 86,768	$ 12,545	0.19
PUT-CALL 66%	$ 84,320	$ 12,388	0.42
PUT-CALL 33%	$ 87,022	$ 13,187	0.62

* Skewness divided by standard deviation cubed, $\frac{E(x-m)^3}{s^3}$.

Table 3. The Means and Standard Deviations for the Strategies Simulated with the Crop and Hog Farm Model.

Strategy	Mean	Standard Deviation	Coefficient of Skewness
‡naïve	$ 587,863	$ 102,032	0.59
APH	$ 581,152	$ 101,044	0.63
CRC	$ 578,998	$ 99,895	0.68
GRP	$ 580,948	$ 101,511	0.61
HF	$ 587,398	$ 108,998	0.63
HO	$ 585,347	$ 90,324	0.61
‡*HH	$ 586,801	$ 75,617	0.11
HC	$ 586,685	$ 81,197	0.23
CO	$ 584,502	$ 95,211	0.62
APH HC	$ 579,974	$ 79,733	0.28
APH CO	$ 577,791	$ 94,062	0.68
GRP HC	$ 579,770	$ 80,283	0.26
GRP CO	$ 577,587	$ 94,567	0.64
APH HO	$ 578,636	$ 89,123	0.67
‡*APH HH	$ 580,090	$ 74,101	0.15
‡HC HH	$ 585,623	$ 75,452	-0.01
HC HF	$ 586,220	$ 83,927	0.32
‡HF HH	$ 586,336	$ 79,168	0.18
HF HO	$ 584,882	$ 96,328	0.70
APH HC HH	$ 578,865	$ 73,585	0.03
APH HC HO	$ 577,458	$ 74,111	0.11
‡*APH HC HH HF	$ 578,447	$ 70,519	0.06
CRC HF HH	$ 577,471	$ 76,771	0.26

* Indicates Membership in SSDRA Efficient Set

‡ Indicates Membership in SSD Efficient Set

Table 4. Correlation Matrix for the Rankings Produced by the Various Ranking Criteria: AgRisk Simulation.

	Sharpe Ratio	VAR_{10}	*Nfsdra*	*Nssdra*	$\rho = 0.5$ $\alpha = 0 - 4$	$\rho = 1$ $\alpha = 0 - 4$	$\rho = 1.5$ $\alpha = 0 - 4$	$\rho = 4$ $\alpha = 0 - 4$
Sharpe Ratio	1.00							
VAR_{10}	0.77	1.00						
Nfsdra	0.79	0.98	1.00					
Nssdra	0.76	0.92	0.92	1.00				
$\rho = 0.5$ $\alpha = 0 - 4$	0.47	0.68	0.68	0.74	1.00			
$\rho = 1$ $\alpha = 0 - 4$	0.53	0.76	0.76	0.82	0.97	1.00		
$\rho = 1.5$ $\alpha = 0 - 4$	0.63	0.86	0.86	0.93	0.90	0.97	1.00	
$\rho = 4$ $\alpha = 0 - 4$	0.71	0.86	0.86	0.96	0.65	0.73	0.85	1.00

Table 5. Correlation of the Rankings Produced by the Ranking Criteria and All Certainty Equivalent Criteria: AgRisk Simulation.

	Sharpe Ratio	VAR_{10}	*Nfsdra*	*Nssdra*
ρ = 0.5 α = 0 – 1	0.27	0.55	0.55	0.62
ρ = 0.5 α = 0 – 2	0.37	0.63	0.63	0.69
ρ = 0.5 α = 0 – 3	0.47	0.68	0.68	0.74
ρ = 0.5 α = 0 – 4	0.47	0.68	0.68	0.74
ρ = 1 α = 0 – 1	0.37	0.63	0.63	0.69
ρ = 1 α = 0 – 2	0.47	0.68	0.68	0.74
ρ = 1 α = 0 – 3	0.51	0.73	0.73	0.77
ρ = 1 α = 0 – 4	0.53	0.76	0.76	0.82
ρ = 1.5 α = 0 – 1	0.47	0.68	0.68	0.74
ρ = 1.5 α = 0 – 2	0.51	0.73	0.73	0.77
ρ = 1.5 α = 0 – 3	0.63	0.85	0.85	0.91
ρ = 1.5 α = 0 – 4	0.63	0.86	0.86	0.93
ρ = 4 α = 0 – 1	0.63	0.85	0.85	0.91
ρ = 4 α = 0 – 2	0.75	0.93	0.93	0.98
ρ = 4 α = 0 – 3	0.77	0.90	0.88	0.98
ρ = 4 α = 0 – 4	0.71	0.86	0.86	0.96

Table 6. Correlation Matrix of Rankings Produced by Various Ranking Criteria: Crop and Hog Farm Simulation.

	Sharpe Ratio	VAR_{10}	*Nfsdra*	*Nssdra*	$\rho = 0.5$ $\alpha = 0 – 4$	$\rho = 1$ $\alpha = 0 – 4$	$\rho = 1.5$ $\alpha = 0 – 4$	$\rho = 4$ $\alpha = 0 – 4$
Sharpe Ratio	1.00							
VAR_{10}	0.99	1.00						
Nfsdra	0.99	0.96	1.00					
Nssdra	0.99	0.98	0.99	1.00				
$\rho = 0.5$ $\alpha = 0 – 4$	0.49	0.49	0.49	0.46	1.00			
$\rho = 1$ $\alpha = 0 – 4$	0.79	0.79	0.77	0.76	0.89	1.00		
$\rho = 1.5$ $\alpha = 0 – 4$	0.91	0.92	0.90	0.90	0.74	0.94	1.00	
$\rho = 4$ $\alpha = 0 – 4$	0.94	0.91	0.96	0.96	0.32	0.65	0.81	1.00

Table 7. Correlation of the Rankings Produced by the Ranking Criteria and All Certainty Equivalent Criteria: Crop and Hog Farm Simulation.

	Sharpe Ratio	VAR_{10}	*Nfsdra*	*Nssdra*
$\rho = 0.5$ $\alpha = 0 - 1$	0.27	0.27	0.26	0.23
$\rho = 0.5$ $\alpha = 0 - 2$	0.39	0.40	0.38	0.36
$\rho = 0.5$ $\alpha = 0 - 3$	0.44	0.44	0.43	0.40
$\rho = 0.5$ $\alpha = 0 - 4$	0.49	0.49	0.49	0.46
$\rho = 1$ $\alpha = 0 - 1$	0.42	0.43	0.41	0.38
$\rho = 1$ $\alpha = 0 - 2$	0.55	0.55	0.54	0.52
$\rho = 1$ $\alpha = 0 - 3$	0.71	0.71	0.70	0.69
$\rho = 1$ $\alpha = 0 - 4$	0.79	0.79	0.77	0.76
$\rho = 1.5$ $\alpha = 0 - 1$	0.53	0.53	0.53	0.50
$\rho = 1.5$ $\alpha = 0 - 2$	0.77	0.77	0.75	0.74
$\rho = 1.5$ $\alpha = 0 - 3$	0.88	0.88	0.87	0.87
$\rho = 1.5$ $\alpha = 0 - 4$	0.91	0.92	0.90	0.90
$\rho = 4$ $\alpha = 0 - 1$	0.90	0.90	0.88	0.88
$\rho = 4$ $\alpha = 0 - 2$	0.97	0.96	0.96	0.97
$\rho = 4$ $\alpha = 0 - 3$	0.97	0.96	0.98	0.99
$\rho = 4$ $\alpha = 0 - 4$	0.94	0.91	0.96	0.96

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