THE IMPORTANCE OF FINANCIAL LEVERAGE AND RISK AVERSION IN RISK MANAGEMENT STRATEGY SELECTION

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Financial Leverage, Risk Aversion, and Risk Management

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ABSTRACT: The problem of choice among risk management strategies is addressed with the stochastic dominance with a risk free asset (SDRA) criteria. The SDRA criteria consider all possible combinations of the strategies and financial leverage. This consideration allows the possibility that strategies with less business risk, less expected return, and greater leverage may dominate strategies with greater business risk and greater expected return. Results show that the inclusion of the risk free asset significantly improves the discriminatory power of the ordinary SD criteria.

Introduction

Income uncertainty affects the welfare of agricultural producers. Academics have suggested that producers respond to income uncertainty by adopting the practice of risk management. Risk management can be viewed as a three-stage process of identification, assessment, and implementation. The manager must first identify practices or strategies that could possibly alter the distribution of monetary returns associated with a production or investment activity. At the assessment stage, the manager must assess the impact of the identified practice(s) on the distribution of returns. Finally, he/she must choose the alternative that produces the most desirable distribution of returns and implement that strategy or practice.

Considerable effort has been devoted to the first two stages of risk management. Many research and extension programs have identified alternative risk management

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strategies and probabilistic outcome information on these strategies (Schnitkey, Miranda, and Irwin; Baker and Patrick, Iowa State, Harwood, et al.). However, there has been much less assistance provided to producers in choosing among the various strategies identified and assessed in the first two stages of risk management.

This paper addresses the problem of choice among risk management alternatives. The results give an indication of the importance of alternative assumptions about economic behavior in risk management contexts and give direction for future work in risk management research and education. The next section briefly discusses the shortcomings of several common economic frameworks used to evaluate risk management strategies and the need for the acknowledgement of financial leverage. Then, the stochastic dominance with a risk free asset (SDRA) risk efficiency criteria are presented and discussed. Next, results comparing the ordinary SD criteria and the SDRA criteria are presented. Finally, conclusions about the importance of financial leverage and the SDRA rules are given.

Choosing Among Risk Management Alternatives

Recently, researchers have spent little time developing methods to assist producers in their choice among risk management strategies. This approach is reasonable given that choice among strategies generally requires knowledge of individual risk preferences. A lack of knowledge regarding the specific functional forms or parameters of individual utility functions makes direct expected utility maximization an undesirable approach for considering individual choice of risk management strategies. However, with the relatively inoffensive assumptions that producers prefer more wealth to less and are risk averse, one can implement the first and second degree stochastic dominance (SD) rules (Fishburn, Hadar and Russell, Hanoch and Levy).

While the generality of the risk preference assumptions supporting the SD rules is appealing, their ability to discriminate between risky alternatives is typically low. This lack of discriminatory power is magnified in risk management contexts because the ordinary SD rules cannot typically discriminate between alternatives which present the agent with a risk for expected return trade-off, e.g., crop insurance and hedging.

Two common failings of the SD rules make them undesirable efficiency criteria for comparing risk management strategies. The common failings are the difference of means and the lower tail crossing problems. The difference of means problem manifests itself by requiring that the mean of the dominating distribution be at least as large as the mean of the dominated distribution. The lower tail crossing problem rules out dominance of the alternative with the largest cumulative probability at the worst possible outcome. Unfortunately, risk management strategies often suffer from the equality of means problem as they present the decision maker with a trade-off of expected return for risk reduction. On the other hand, base strategies often suffer from the lower tail crossing problem. This means that the traditional SD rules are not usually empirically efficient tools for evaluating risk management strategies because the efficient sets tend to be large. Because the efficient sets associated with the ordinary SD criteria are typically large, researchers sought to refine the criteria. The refinements typically strengthened the ordinary SD criteria by more thoroughly specifying risk preferences.

Meyer's generalization of the SD criteria made it possible to strengthen the ordinary SD criteria by narrowing the range of risk aversion covered by decision rules such as SSD. This method allows the researcher to specify a range in which the coefficient of absolute risk aversion lies. By reducing the permissible range of the coefficient of absolute risk aversion (ordinary SSD assumes that the coefficient of absolute risk aversion lies in the interval from zero to positive infinity), one can strengthen the SSD criterion. This procedure is similar to direct expected utility maximization in that one is making assumptions regarding the magnitude of the utility function's parameter. Unfortunately, there is little agreement regarding the proper range of the coefficient of absolute risk aversion (Cochrane and Raskin). As a result, McCarl suggested that a more appropriate procedure was to identify the level of absolute risk aversion at which preferences for prospects switch (1988, 1990). Regardless, when ordinary SSD does not exist, both methods require that the researcher specify risk preferences beyond that of risk aversion.

The Importance of Financial Risk

Rather than refining the ordinary SD criteria by assuming a smaller relevant range for the coefficient of absolute risk aversion, the SDRA criteria refine ordinary SD by recognizing that agents have access to financial leverage. This is an important extension in risk management contexts because previous research has shown a clear relationship between financial leverage and the use of risk management products (Shapiro and Brorsen; Moss, Ford, and Castejon; Turvey and Baker 1989, 1990; Collins 1997). For instance, Collins (1997) showed that models incorporating variables for the financial structure of the firm could potentially explain hedging behavior.

Collins (1985) also developed a model that explained how a producer might manage risk by adjusting both business and financial risk. Most common risk management tools are designed to control business risks, e.g., price hedging and output insurance. Financial risks are adjusted by varying the proportion of debt funds used to finance the business. Debt funds "leverage" the return to equity funds by magnifying both positive and negative returns. Thus, a producer might use risk management tools to reduce business risk and consequently expected return. To compensate for the reduced expected return, the producer may slightly leverage the expected return of the risk managed investments with debt funds.

The ordinary SD criteria are only capable of identifying strategies that are business risk efficient for a particular level of leverage. The SDRA criteria developed by Levy and Kroll (1978) extend SD's characterization of risk to include financial risk. When discussing the usefulness of the SDRA criteria in the context of evaluating the performance of various mutual funds Levy and Kroll (1979, pg. 130) find an "empirical separation" is generated by the SDRA rules. For instance, the second degree SDRA (SSDRA) set contained from 1.5 percent to 18 percent of the mutual funds evaluated over different time horizons, while the SSD set contained 9 percent to 41 percent of the funds. Thus, by recognizing an agent's ability to alter financing, one is able to reduce the number of investments deserving managerial attention.

The value of the empirical separation is important where it is not appropriate to apply more commonly used risk efficiency models such as the mean-variance and the mean-variance with a risk free asset (the Sharpe ratio) models (Markowitz, Sharpe). These models are dependent upon the assumption that the return distributions being compared differ by only the first two moments. The SDRA criteria are not contingent upon this assumption, and allow for a much more thorough characterization of the riskiness of an investment. The criteria are especially well suited to evaluate risk management alternatives such as option strategies that affect higher moments of the distribution of returns.

The Risk Free Asset

SDRA is contingent upon the existence of an asset with a risk free return, i.e., no variance in return, that can be traded with no transaction costs. Johnson noted that risk free assets exist in agriculture. The important characteristic of such an asset is that its returns are not variable over the time frame the agent is making her/his investment. Turvey, Baker, and Weersink used cash rental of farmland (in and out) as a risk free asset. Likewise, borrowing money from a financial institution generates an obligation that must be repaid with certainty. Because the time frame for managing production risks is one year, the agent observes the cash lease rate or the borrowing rate and fixes it. By initially assuming that the borrowing and lending rates are equal, one can examine the SDRA criteria's potential to narrow the risk efficient set in risk management contexts.

Stochastic Dominance with a Risk Free Asset

The derivation and proof of the necessity and sufficiency of the SDRA rules for ranking risky projects can be found in Levy and Kroll (1978) and Levy (1998). The rules are derived by constructing combinations of the returns to risky actions and the return to the risk free action. Consider the case where there are two risky outcomes *X* and *Y*, and a risk free outcome *r*. Following Levy and Kroll (1978) the risky outcomes can be combined with the risk free outcome as shown in (1) and (2).

(1) $$X_{\alpha} = (1-\alpha)r + \alpha X \ , \qquad \alpha \in [0, \infty)$$

(2) $$Y_{\beta} = (1-\beta)r + \beta Y \ , \qquad \beta \in [0, \infty)$$

where X_{α} and Y_{β} are the sets of all combinations of the risky outcome and the risk free return, α and β are weights of the original risky outcomes *X* and *Y* in these combinations, and *r* is the risk free return. Each outcome in the set X_{α} or Y_{β} has an associated cumulative distribution function (CDF). The sets of CDF's can be denoted $F_{X\alpha}$ and $G_{Y\beta}$, where any particular element in $F_{X\alpha}$ or $G_{Y\beta}$ has the form shown in (3) and (4). That is,

(3) $$F_{X\alpha 0}(z) = \Pr(X_{\alpha 0} \leq z)$$

(4) $$G_{Y\beta 0}(z) = \Pr(Y_{\beta 0} \leq z)$$

where z is some monetary outcome and *Pr* returns the probability that $X_{\alpha 0}$ or $Y_{\beta 0}$ is less than or equal to z.

Borrowing the risk free asset (α>1) pivots the CDF of the original strategy clockwise around the risk free return. In Figure 1, the solid CDF represents the original, unleveraged CDF associated with action *X*. The dashed line shows one potential CDF that might be generated by borrowing the risk free asset, α >1. When α is greater than 1, the agent invests in negative amounts of the r, i.e., borrows at the risk free rate of return. The agent then invests these borrowed funds in the risky asset, X. When the returns to the activity are greater than the risk free return, the agent gains a net profit from borrowing and adds this to the original return. Thus, the cumulative probability is lower at outcomes above the risk free return, r. When the return is less than the risk free return, the agent accepts a net loss from borrowing and must repay the funds borrowed at the risk free return from the returns to the risky activity. This loss is subtracted from the original return to X and increases the probability of outcomes below the risk free return. Similarly when the agent lends the risk free asset, $0 \leq \alpha < 1$, the CDF pivots counter clockwise around the risk free return.

The SDRA rules are developed by realizing that the ordinary SD rules can be restated in quantile notation (see Chapter 4 of Levy 1998 for a thorough discussion of the quantile formulation of both the ordinary SD and SDRA criteria). The quantile function is the inverse of the cumulative distribution function. Define the set of quantile functions for X_α and Y_β as (5) and (6).

$$Q_{F\alpha}(p) = F_{X\alpha}(x)^{-1} = (1-\alpha)r + \alpha Q_F(p) \quad (5)$$

$$Q_{G\beta}(p) = G_{Y\beta}(x)^{-1} = (1-\beta)r + \beta Q_G(p) \quad (6)$$

where $Q_{F\alpha}(p)$ and $Q_{G\beta}(p)$ are the sets of quantile functions associated with the cumulative distribution functions for the leveraged activities X and Y respectively, p is cumulative probability, x is a monetary outcome level, α and β are the proportion of the investment in risky activities X and Y, and $Q_F(p)$ and $Q_G(p)$ are the inverse of the cumulative distribution functions for the unleveraged activities X and Y.

The condition for dominance of $F(x)$ over $G(x)$ by ordinary FSD is given by (7) and preference by ordinary SSD is shown in (8).

(7) $Q_F(p) - Q_G(p) \geq 0 \quad \forall p \in [0,1]$ with at least one strict inequality

(8) $\int_0^p [Q_F(t) - Q_G(t)]dt \geq 0 \quad \forall p \in [0,1]$ with at least one strict inequality

where $Q_F(p)$ and $Q_G(p)$ are the quantile functions for activities associated with the CDF's $F(x)$ and $G(x)$, p is cumulative probability, and t is a variable of integration.

Levy and Kroll prove that if one can find an element in $F_{X\alpha}$ that dominates G_Y (the unlevered CDF of activity Y) then it will always be possible to find a CDF in $F_{X\alpha}$ that dominates every CDF in $G_{Y\beta}$ (1978, pg. 556 for FSD, and pg. 561 for SSD).

That is, for first degree stochastic dominance with a risk free asset (FSDRA) one must find a value of α for which (9) holds and for second degree stochastic dominance with a risk free asset (SSDRA) (10) must hold.

(9) $Q_{F\alpha}(p) - Q_G \geq 0 \qquad \forall p \in [0,1]$

(10) $\int_0^1 [Q_{F\alpha}(t) - Q_G(t)]dt \geq 0 \qquad \forall p \in [0,1]$

which are restatements of the ordinary SD rules in (7) and (8) with the leverage variable α included. Levy and Kroll (1978) prove that if an α exists such that (9) and/or (10) holds, then for each CDF in $G_{Y\beta}$ one will always be able to find a CDF in $F_{X\alpha}$ which dominates it by FSD and/or or SSD. Thus, if (9) holds the decision maker who prefers more wealth to less and has access to financial leverage would strictly prefer investment X to investment Y. If only (10) holds, any decision maker who is risk averse and has access to financial leverage would prefer X to Y. On the other hand, if no α exists for which (9) and/or (10) holds, neither FSDRA nor SSDRA of $F(x)$ over $G(x)$ exists. By substituting (5) into (9) and solving for α one obtains the FSDRA rule given by (11), which Levy and Kroll (1978) prove is a necessary and sufficient condition for FSDRA (1978, pg. 558 or Levy 1998 Chapter 4).

$$(11) \qquad \inf_{0 \le p < F(r)} \frac{Q_G(p) - r}{Q_F(p) - r} \ge \sup_{F(r) < p \le 1} \frac{Q_G(p) - r}{Q_F(p) - r},$$

where *inf* represents the infimum, or greatest lower bound, p is probability, $F(r)$ is the cumulative distribution function of investment X evaluated at the risk free rate, $Q_F(p)$ and $Q_G(p)$ are the quantile functions for investment X and Y, r is the risk free return, and *sup* is the supremum, or least upper bound. The necessary and sufficient condition for SSDRA is obtained by using (5) and (10) and solving for α (Levy and Kroll, 1978 pg. 566 or Levy 1998 Chapter 4). Formally, the SSDRA rule is given by (12):

$$(12) \qquad \inf_{0 \le p < p_0} \frac{\int_0^p [Q_G(t) - r]dt}{\int_0^p [Q_F(t) - r]dt} \ge \sup_{p_0 < p \le 1} \frac{\int_0^p [Q_G(t) - r]dt}{\int_0^p [Q_F(t) - r]dt} \qquad ,$$

where p_0 solves (13)

$$(13) \qquad rp_0 = \int_0^{p_0} Q_F(t)dt ,$$

and everything is as before with the exception of p_0, which is new. The cumulative probability level p_0 replaces the cumulative probability associated with the risk free return, *F(r)*, as the bounds of the infimum and supremum problem and is the value at which the denominators in (12) are equal to zero.

A Graphical Interpretation of FSDRA

The SDRA conditions can be interpreted as a method to find the amount of pivoting needed to induce ordinary SD dominance above (below) the boundary of the supremum and infimum problems relative to the amount of pivoting that is allowed below (above) this point. Figure 2 shows one possible case. Here the solid CDF, *G(x)*, might represent the returns to a base strategy such as using the natural hedge, and the dashed CDF, *F(x)*, could represent the returns to a risk management strategy such as buying crop insurance. It is assumed that the expected value of the risk management strategy is less than the expected value of the base strategy. Therefore, *F(x)* cannot dominate *G(x)* by ordinary SSD. Because *G(x)* has a larger probability at the smallest outcome it cannot dominate *F(x)* by any degree of ordinary SD.

Define the values of *a*, *b*, *c*, and *d* with the ratios shown in (14) and (15) to correspond to the terms in the necessary and sufficient condition for FSDRA given by (11):

(14) $$\frac{a}{b} = \frac{Q_G(p) - r}{Q_F(p) - r} \forall p \in [0, F(r)) \text{ and}$$

(15) $$\frac{c}{d} = \frac{Q_G(p) - r}{Q_F(p) - r} \forall p \in (F(r), 1].$$

In the case shown in Figure 2, below *F(r)* the solution to the infimum is always greater than one as *b* is less than *a*. The smallest value of *a/b* will occur where *b* is the greatest proportion of *a* or where the distance $Q_G(p) - Q_F(p)$ is minimized. Because the infimum is greater than one, if FSDRA exists in this case, positive amounts of leverage must be used to induce dominance below the risk free return. In this case, one can interpret the solution to the infimum as the most leverage that can be added to the risk management strategy without producing a lower tail crossing.

The supremum problem for the case depicted contains three ranges to discuss. In the probability interval above $F(r)$ up to $G(r)$, the ratio, c/d, is negative, as $Q_F(p) - r$ is always positive, and $Q_G(p) - r$ is always negative. Above $G(r)$, but below the intersection of the CDFs denoted on the probability axis as p^*, the ratio is less than one as d is greater than c. After the distributions cross, the ratio will be greater than one as d is less than c. Thus, the solution to the supremum problem will occur when d is the smallest proportion of c, or when $Q_G(p) - Q_F(p)$ is maximized at probabilities above $F(r)$. In this case, the solution to the supremum problem identifies the largest distance that the CDF must be pivoted to induce FSD above r. The requirement that the infimum be greater than the supremum insures that the allowed negative impact of leverage in the lower tail must be greater than the required positive impact of leverage in the upper tail. In other words, the amount of room available to pivot $F(x)$ must be greater than the amount of pivoting needed.

The above case demonstrates that SDRA allows one to rank two strategies with different means in which the strategy with the smaller mean and less business risk dominates. Although not possible in the case depicted, it is also possible for a strategy with a larger mean and larger probability at the smallest outcome (a base strategy) to dominate a strategy with a smaller mean and smaller probability at the smallest outcome (a risk management strategy). This can be accomplished by lending ($0 \leq \alpha < 1$) enough of the risk free asset, *r*, to pull the lower tail of the CDF of the base strategy below the lower tail of the CDF of the risk management strategy.

Data

Two risk management simulation models were used to generate the distributions compared with the rules. The simulation models represent work associated with the identification and probabilistic assessment stages of risk management. Both were designed to assist agricultural producers in determining the probabilistic impact of risk management strategies on the distribution of gross revenues. The AgRisk model is currently available as an extension tool from The Ohio State University. The data were generated with a modified version of AgRisk that output the probability density functions for each simulated alternative. In the AgRisk case, 13 risk management marketing strategies were simulated for a 300 acre corn and soybean farm in Decatur county Indiana. The probability density functions contained roughly 4,500 observations with unequal probability weights. 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 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 probability distributions consisted of 799 observations with equal probability weights. 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.

Algorithms based upon the SD rules given by (7) and (8) and the SDRA rules given by (11), (12), and (13) were written in the IML procedure of SAS V6.12. Different algorithms were necessary for the cases of equal and unequal probabilities. Copies of these algorithms are available from the authors.

The Results

Table 4 shows the number of strategies and the percent of strategies contained by the FSD, SSD, FSDRA, and SSDRA efficient sets for both simulations. In both cases all of the strategies were included in the FSD efficient set. Application of the SSD criterion reduced the number of strategies that must be considered by 54 percent (the SSD set) in the AgRisk case and 74 percent in the crop and hog simulation.

The results show that the assumption of risk aversion discriminates more strongly in the crop and hog simulations. The difference in discriminatory power is partially explained by the different number and types of strategies simulated with the models. The AgRisk case only considered marketing strategies, while the results from Nydene's model considered output quantity and output price activities. Further, all of the hedging techniques simulated in Nydene's work placed hedges on 100 percent of expected production, a practice that tended to be inefficient in both the AgRisk and crop and hog simulations.

The efficient sets suggested by the SDRA criteria are noticeably smaller than the FSD and SSD efficient sets. In both cases, the FSDRA efficient set contains only one more strategy than the ordinary SSD efficient set. In both cases, the assumption of access to leverage is nearly as powerful as the assumption that decision makers are risk averse. When access to leverage and risk aversion are both assumed, (the SSDRA criterion) the efficient set contained 4 of the 13 AgRisk strategies and 3 of the 23 crop and hog strategies.

In the AgRisk case, SSDRA removed 2 strategies from the SSD set, Fwd 66% and the natural hedge. The natural hedge strategy was guaranteed to be in the SSD set because it had the largest mean return. However the natural hedge strategy was dominated in a SSDRA sense by several strategies. Figure 3 demonstrates that when one recognizes the ability to adjust risk and return with financial leverage the natural hedge strategy is shown to have an inefficient amount of business risk.

Figure 3 shows the results for the two ordinary SSD comparisons shown in (14) and (15).

$$(14) \qquad \int_0^1 Q_{Fwd\,33\%}(p)dt - \int_0^1 Q_{NaturalHedge}(p)dt = \text{Cumulative Area Difference}$$

$$(15) \qquad \int_0^1 Q_{LevFwd\,33\%}(p)dt - \int_0^1 Q_{NaturalHedge}(p)dt = \text{Cumulative Area Difference}$$

where $Q_{Fwd33\%}$ represents the quantile function for a particular risk management strategy, forward contract 33 percent of expected production, $Q_{NaturalHedge}$ represents the quantile function of the natural hedge strategy, cash sale at harvest, and $Q_{LevFwd33\%}$ represents the quantile function of the risk management strategy leveraged by borrowing 10 percent of the risk free asset.

Figure 3 shows a graph of these comparisons at every probability level. For dominance to exist the curve must not intersect the cumulative probability axis. The comparison in (14) (forward contract 33% of expected production versus natural hedge) shows that the risk management strategy gains an early cumulative area surplus and SSD is not ruled out until the 97 percent cumulative probability level. On the other hand, the curve showing the comparison in (15) (forward contract 33 percent of expected production leveraged at 10% versus the natural hedge) shows that by leveraging the forward contracting strategy the cumulative difference initially shrinks, but remains positive over the entire range of probability. Leveraging the risk management strategy has the effect of reducing returns below the risk free return and increasing them above the risk free return. Because the increase in returns above the risk free return cause the area difference to increase faster than the cumulative area difference below the risk free return shrinks, SSD emerges when leverage is applied.

Summary

The results lead to several conclusions. The most apparent is that the acknowledgement of access to financial leverage is important when making risk management strategy selections. In both cases this recognition alone caused a reduction of the FSD set nearly as large as the reduction caused by recognizing risk aversion. These results indicate that risk management decisions should not be made without considering the impact of financial leverage.

While the acknowledgement of access to financial leverage is important when selecting risk management strategies, risk aversion is also important. By combining these two assumptions one can reduce the set of strategies that merit managerial attention. In the two simulations conducted, combining these assumptions reduced the number of strategies to be considered by 87 and 69 percent.

The SDRA results are important because they reduce the number of strategies that managers must consider. This reduction can simplify the farm manager's choice among risk management strategies without making strong assumptions about risk preferences. Unlike other refinements of the ordinary SD rules, the reduction is obtained by recognizing that financial leverage can be used to increase the mean return of strategies that contain relatively small amounts of business risk. In many cases, (where SDRA exists) adding leverage is a more efficient way to increase return than reverting to a strategy with a greater mean and greater business risk. More importantly, because decision makers have access to financial leverage, SDRA analysis of risky projects is more complete than analyses conducted without recognizing the role of financial leverage. These results indicate that at least as much effort should be devoted to educating producers about the impacts of, and selection of leverage levels as is devoted to the selection of traditional risk management strategies such as hedging.

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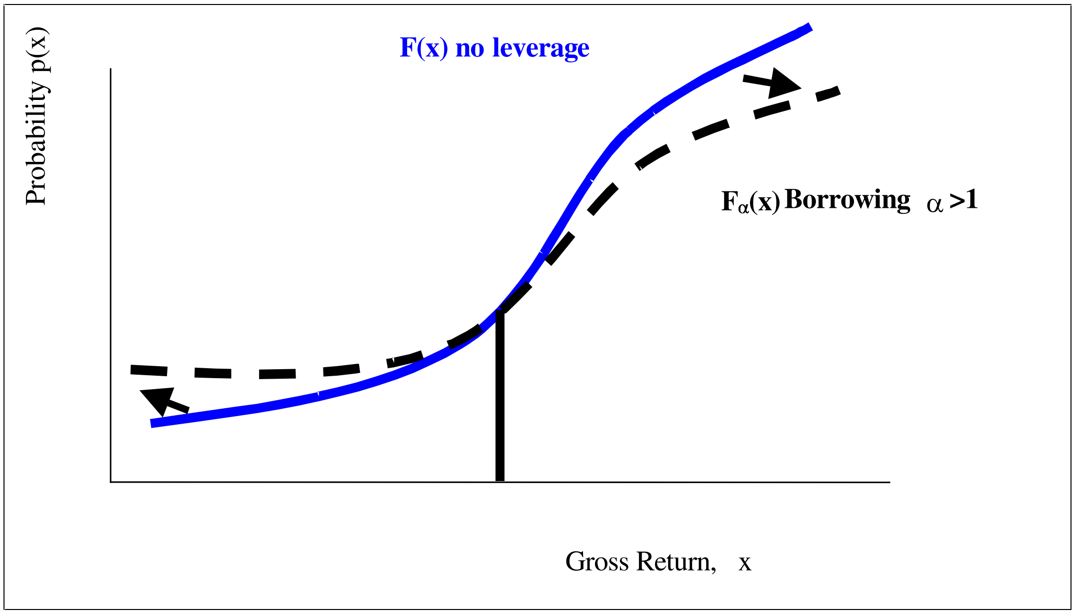

Figure 1. The effect of borrowing the risk free asset on the cumulative distribution function.

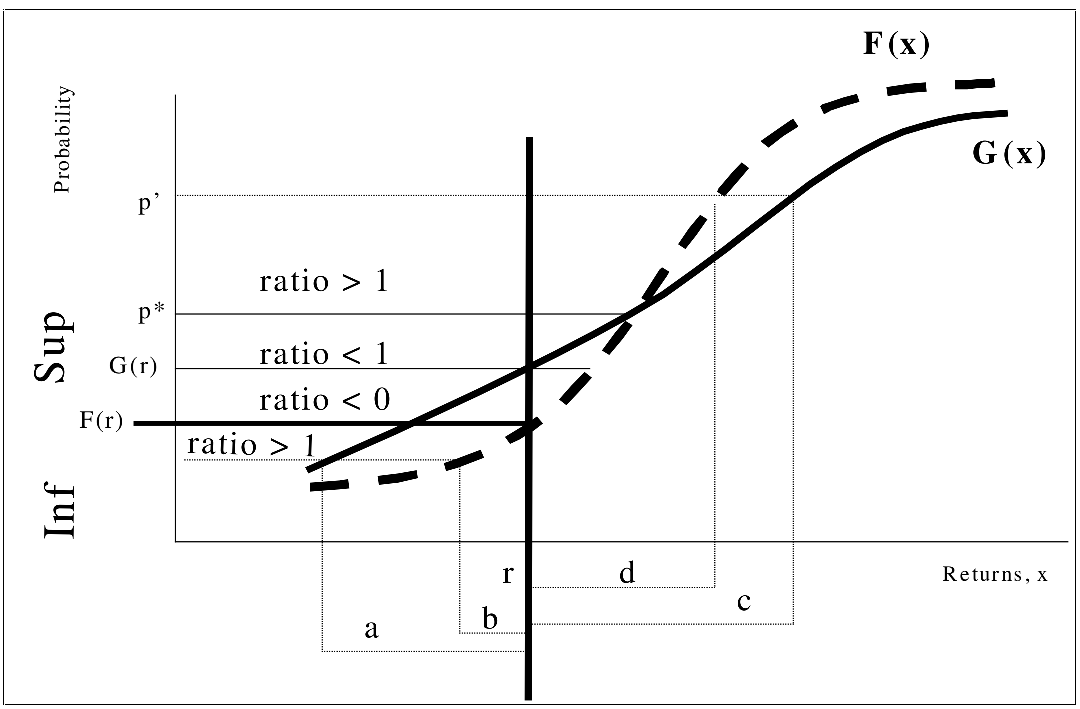

Figure 2. A graphical interpretation of the necessary and sufficient conditions for FSDRA.

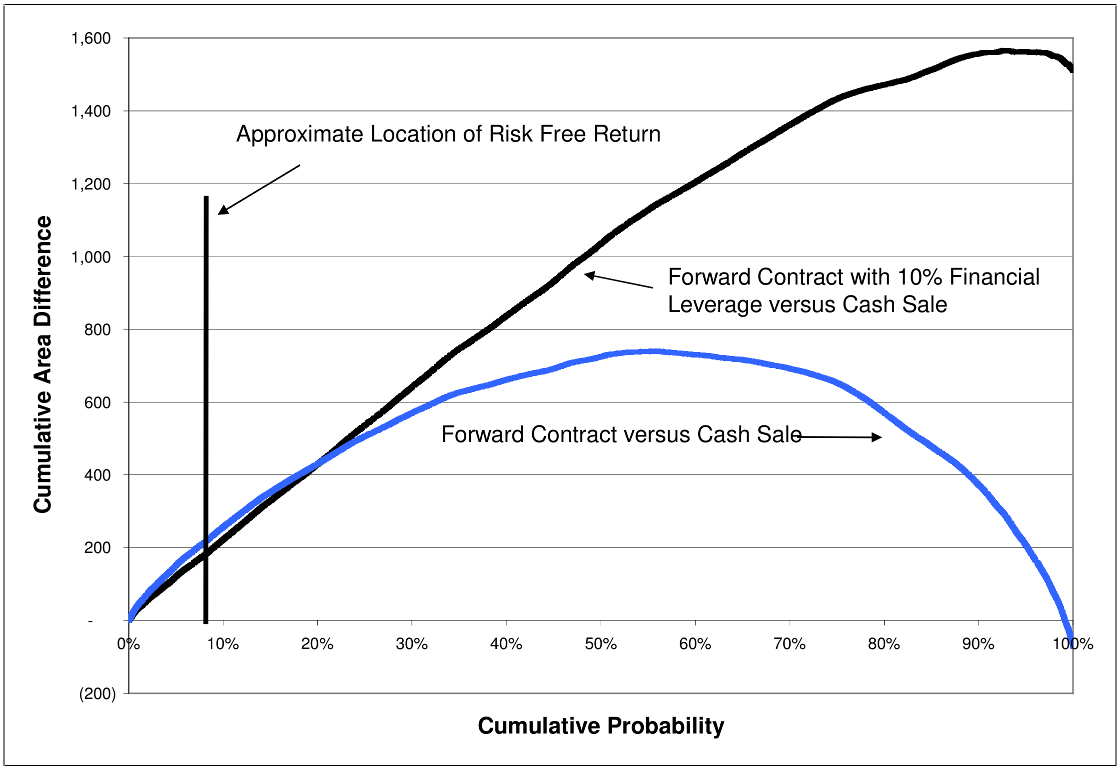

Figure 3. Cumulative area differences for SSD comparisons.

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

* Indicates Membership in SSDRA Efficient Set
‡ Indicates Membership in SSD Efficient Set

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

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

Strategy	Mean	Standard Deviation	Standardized 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: The size of the ordinary SD and SDRA efficient sets.

Simulation	FSD	SSD	FSSDRA	SSDRA
AgRisk: Number in Set	13	6	7	4
Percent of Total Strategies	100%	46%	54%	31%
Crop and Hog: Number in Set	23	6	7	3
Percent of Total Strategies	100%	26%	30%	13%