EFFICIENCY CRITERIA AND RISK AVERSION: AN EMPIRICAL EVALUATION

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Abstract

A conceptual link among mean-variance (EV), stochastic dominance (SD), mean-risk (ET), and Gini mean difference (EG) is established for determining risk efficient decision sets. The theoretical relations among the various efficiency criteria are then empirically demonstrated with a soybean and wheat double-crop simulation model. Empirical results associated with extended Gini mean difference (EEG) and extended mean-absolute Gini (EEΓ) for risk analysis are encouraging.

Key words: risk, efficiency criteria, Gini mean difference.

In situations with unknown preferences, a risk efficient set of decisions is determined based on an assumed preference relation and various approximations of decision probability distributions. Numerous efficiency criteria specifying restrictions on preferences and probability distributions are prevalent in the literature. Efficiency criteria popular in agricultural economics literature include mean-variance (EV) and stochastic dominance (SD) analyses, whereas mean-risk (ET) and Gini mean difference (EG) analyses are generally less popular (Yitzhaki, 1982).

A necessary condition for one distribution to dominate another, common to all of these criteria under risk aversion, is expected value analysis where a comparison of the first moment of the decision density functions is performed. Necessary and sufficient conditions for various efficiency criteria differ based on their representation of a risk function—a measure of dispersion unique to each criterion. Specifically, variance of a density function is employed in EV, modified semivariance in ET, and Gini mean difference in EG analysis. Variation in risk preference assumptions are incorporated into a risk function by changing r, the Pratt-Arrow risk aversion coefficient in SD analysis, and α, the exponent conditioning the degree to which segments of the associated density functions are to be emphasized in ET and EG analyses.

The objective of this paper is first to present a collection of general results which provide a conceptual link among the efficiency criteria, and to demonstrate empirically the varying degrees of similarity among the criteria. Recommendations on the appropriate efficiency criteria based on research objectives are provided in a concluding section.

EFFICIENCY CRITERIA

Expected Value (EV) and Stochastic Dominance (SD)

Markowitz's EV analysis which employs the first two moments of a density function as the criterion for ranking decisions is extensively employed in the agricultural economics literature. The efficiency criteria determining EV for any two distributions F and G is that F dominates G if $\mu_F \geq \mu_G$ and $\sigma^2_F \leq \sigma^2_G$ hold with at least one strict inequality, where μ and σ^2 denote a distribution's mean and variance, respectively. Unfortunately, EV analysis may lead to unwarranted conclusions when the assumptions of normality or a quadratic utility function are violated. EV analysis penalizes decisions equally for deviations above and below the expected value which can be a shortcoming given an asymmetric distribution (Selley).

Baumol amends Markowitz's analysis by explicitly considering confidence limits. The risk involved in a given action choice is represented by k standard deviations, σ, from the mean, μ, with k indicating the degree of risk

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aversion chosen by the decision maker. Specifically, $\mu - k\sigma$ may be considered the lower confidence limit for the variation in question. The more conservative the confidence limit criterion, increasing k, the greater the degree of risk aversion. Baumol's efficiency criteria state that F dominates G if $\mu_F \geq \mu_G$ and $\mu_F - k\sigma_F \geq \mu_G - k\sigma_G$ hold with at least one strict inequality. Thus, in contrast to EV analysis, a prospect with a relatively high variance will dominate if its expected value is sufficiently high. The subsequent culling of EV efficient alternatives based on Baumol's criteria will further reduce the efficient set.

Second degree stochastic dominance (SSD) does not impose the restriction of normality or a quadratic utility function and is consistent with Baumol's criteria. A decision with higher variance and mean might be preferred which may further reduce the efficient set. As examples, SSD efficient sets for lognormal and uniform distribution are subsets of the EV efficient sets (Levy; Yitzhaki, 1982). An exception is the case of normal distributions where SSD and EV efficient sets are identical (Levy and Hanoch). However, Porter states that regardless of the density functional form, if two decisions have the same mean (variance) but different variance (mean) and one is inefficient by SSD, then it also is inefficient by EV.

Cochran et al. note that SSD in some cases still leads to a relatively high Type II error, where the hypothesis of no dominance is not rejected when an alternative is in fact dominant. Type II errors generally correspond to large efficient sets. As a method to reduce the efficient set, Meyer has suggested stochastic dominance with respect to a function (SDWRF). SDWRF assumes a decision maker's preference and degree of risk aversion lie within specific Pratt-Arrow bounds. Unfortunately, SDWRF reduces Type II errors by possibly increasing the probability of rejecting the hypothesis of no dominance when such a rejection is unwarranted, a Type I error.

An alternative efficiency criterion is convex stochastic dominance (CSD) (Fishburn, 1974). Unlike SDWRF, CSD does not require additional knowledge of risk preference intervals, because CSD uses the preference interval of the associated efficiency criteria, SSD, SDWRF, or other risk criteria. CSD is a two-step process where first an efficient set is identified for the relevant preference interval, and then CSD is applied to further reduce the efficient set. A convex combination of several action choices is compared to one choice perceived to be *a priori* inferior. Through successive iterations of alternative convex combinations and perceived inferior action choices, a risk efficient set of alternatives results.

Cochran et al. note that CSD lowers the probability of Type II errors without changing the probability of Type I errors. The criterion eliminates alternatives from the efficient set which would not be preferred by any individual in a specified preference interval, but for which no agreement as to alternative superiority exists. CSD implicitly culls those prospects with relatively low means and variances, and, thus, employs the same underlying reasoning for establishment of efficient sets as Baumol. A problem with CSD is determining the choice alternatives that comprise the convex combination and developing an appropriate weighting scheme. Fishburn (1974) suggests that a more significant aspect of CSD is its converse assertions. Instead of identifying an efficient set where at least one of the prospects in the set dominates a prospect not in the set, CSD could be employed to conclude that a set of prospects are not preferred to an alternative set of prospects.

In an application Bawa et al. demonstrate how CSD has the potential to reduce first, second, and third degree stochastic dominant (FSD, SSD, TSD) efficient sets. Cochran et al. demonstrate a reduction in the efficient set by CSD for SDWRF by applying a linear programming algorithm with gridpoints marking off the cumulative probability functions. Such a mathematical programming modeling effort could be cumbersome (Boisvert) and is questionable with the lack of population counterparts supporting stochastic dominant sample estimates. Pope and Ziemer note that failure to consider sampling error in stochastic dominance analysis has led some to argue that the procedures are so unreliable as to warrant a moratorium. Alternatively, a search for more powerful and economical tests for risk efficiency could yield a significantly reduced efficient set and a simple method for determining such a set.

Mean-Risk (ET)

Fishburn (1977) proposes ET analysis as a class of models which are computationally efficient and provide clear implications about risk preference. ET may be generally preferred to EV analysis when the distributions are asymmetric (Selley). The general model for ET analysis is

$$(1)\ F_{\alpha}(t) = \int_{-\infty}^{t} (t-x)^{\alpha}\, dF(x),$$

where F(x) is the probability of obtaining a return not exceeding x and t is a specified target return. The efficiency criteria determining ET for any two distributions F and G are that F dominates G if $\mu_F \geq \mu_G$ and $F_{\alpha}(t) \leq G_{\alpha}(t)$ hold with at least one strict inequality. Variation in the value of the exponent, α, in equation (1) influences the emphasis on specific portions of the distribution. When $\alpha = 2$, equation (1) reduces to mean-semivariance (ES) analysis (Porter). Except for decisions with identical means and semivariances, every decision that is efficient by ES is also efficient by SSD analysis (Porter; Fishburn, 1977). Fishburn's Theorem 3 states that if decision F is FSD over decision G, then F dominates G in terms of ET for all values of $\alpha \geq 0$; if F is SSD over G, then F dominates G in ET analysis for all $\alpha \geq 1$; and if F is TSD, then F dominates G in ET analysis for all $\alpha \geq 2$. As $\alpha \rightarrow 1$, the ET efficient set approaches the risk neutral set associated with the expected value criterion. As $\alpha \rightarrow \infty$ the ET efficient set approaches the criterion of Rawls, which evaluates decisions based on the minimum outcome associated with each decision alternative—the maximum criterion. If $\alpha < 1$, risk prone preferences are assumed.

Recognizing decision makers' desire to reduce the risk of failing to meet a certain target level may make ET analysis appealing. However, a problem with ET analysis is determining the target value t. In applications, t may be a point of zero net returns, a return equivalent to the opportunity cost of the investment, or other *a priori* conditions that specify a target value. Alternatively, a researcher may vary t as a measure of different levels of risk preference. As $t \rightarrow a$, the minimum decision variate, the ES efficient set approaches the risk neutral set associated with the expected value criterion. As t increases, the degree of risk aversion also increases. In the limit as $t \rightarrow b$, the maximum variate, the efficient set approaches the Rawlsian criterion set.

In many cases researchers have no *a priori* information concerning a target level of a decision variate. Resorting to SD analysis may prove inadequate given its more involved nature in comparison with EV and ET. Specifically, SD may require development of an optimization algorithm as in portfolio selection (Cochran et al.; Bey; Yitzhaki, 1983), with the possibility of generating large efficient sets resulting in negligible discriminating power among choice alternatives. Yitzhaki (1982) suggests that Gini mean difference be considered as an efficiency criterion, avoiding the inherent problems of other methodologies.

Gini Mean (EG)

Gini proposed a measure of variability for any statistical distribution based on the average of the absolute differences between pairs of observations. Gini's coefficient is defined as the ratio of half of the average to the mean of the distribution. Specifically, the relative Gini coefficient (G) is

$$(2)\quad G = \triangle/2\mu,$$

$$\text{where } \triangle = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} |x-y|\, dF(x)dF(y),$$

and μ is the distribution mean. The measure of dispersion, $\triangle$, is defined as Gini's mean difference.

The advantage of Gini mean difference over variance has been demonstrated by Yitzhaki (1982). Variance penalizes all first moment deviations, generally relegating choice alternatives with relatively large associated variances into a risk inefficient category. Dispersion arising from a shift to the right of a portion of the distribution may be deemed desirable by a majority of decision makers. Gini's mean difference provides a method to establish risk efficiency among choice alternatives by determining the increase in distribution mean required to offset increasing variance.

The efficiency criteria determining EG for any two distributions F and G is determined by first defining $\Gamma = \triangle/2$ as the absolute Gini. Distribution F then dominates G if $\mu_F \geq \mu_G$ and $\mu_F - \Gamma_F \geq \mu_G - \Gamma_G$ hold with at least one strict inequality (Lerman and Yitzhaki). EG can be directly related to Baumol's expected gains and confidence limits, where Baumol's criteria $k=1$ and σ are replaced by Γ. This criterion is a necessary condition for FSD and SSD, corresponding to Baumol's criteria for EV analysis. EG allows a prospect with higher variance and mean to be preferred. Only two summary statistics are required in calculating EG, making it almost as easily calculated as EV analysis. Alternatively, Γ may replace variance as a measure of variability resulting in the mean absolute Gini criteria (EΓ), where distribution F dominates G if $\mu_F \geq \mu_G$ and $\Gamma_F \leq \Gamma_G$ hold with at least one strict inequality. In fact, EV analysis with the assumption of a normal distribution is a special case of EΓ. Yitzhaki (1982) demonstrates that for normal distributions the relation among efficient sets is

$$\mathrm{EV} = \mathrm{E\Gamma} = \mathrm{SSD} \supseteq \mathrm{EG},$$

where $\supseteq$ specifically denotes EG is a subset of SSD. For lognormal and uniform distributions, the efficient set relation is

$$\mathrm{EV} = \mathrm{E\Gamma} \supseteq \mathrm{SSD} \supseteq \mathrm{EG}.$$

In spite of the above advantages of Gini mean difference, the inconvenience in calculation along with the ease in computing variance have probably contributed to the frequent substitution of other efficiency criteria for the EG method. However, Lerman and Yitzhaki recently developed a simple formula, based on Stuart's work, for calculating and interpreting Gini mean difference. They demonstrate that the only information required is the mean, sample size, and covariance between the variable and the cumulative distribution. Specifically, absolute Gini, Γ, may be defined as

$$(3)\ \Gamma = \int_a^b F(x)[1-F(x)]dx,$$

where a and b are the lowest and highest values of x. Integration by parts, transformation of variables, and noting that F is uniformly distributed between [0,1] with mean of one half, allows equation (3) to be written as

$$(4)\ \Gamma = 2\,\mathrm{cov}[x,F(x)],$$

where cov denotes the covariance operator. Thus, Γ becomes simple to calculate by determining the covariance between x and the corresponding cumulative distribution function, F(x), and multiplying by two.

Lerman and Yitzhaki further illustrate the convenient relation between Γ and slope coefficient, B, from a regression of x on F(x),

$$(4)\ \Gamma = 2B\,\mathrm{var}[F(x)],$$

where var[F(x)] is the variance of F(x). In large samples var[F(x)] converges to a constant so Γ is proportional to the slope coefficient B. Thus, a low (high) Γ implies small (large) changes in the decision variate x. This interpretation gives Γ a more intuitive meaning than other dispersion measures such as variance (Lerman and Yitzhaki).

Buccola and Subaei relate EG analysis to weak risk aversion which may underestimate the risk aversion of decision makers. EG analysis is a powerful discriminator of risky prospects and, similar to expected value analysis, may not fully consider a decision maker's risk preferences. Yitzhaki (1983) illustrates how an extended Gini mean difference criterion (EEG) considers various levels of risk aversion. Specifically,

$$(5)\ \Gamma(\alpha) = \mu - a - \int_a^b [1-F(x)]^{\alpha}dx,$$

(Shalit and Yitzhaki). Γ(2) corresponds to the absolute Gini employed in EG analysis.

Extending EG analysis by EEG explicitly introduces the degree of risk preference as a parameter. The aversion to risk rises as α increases from zero to infinity. From 0 to 1, Γ represents a preference for risk. Risk neutrality is assumed at $\alpha = 1$ which corresponds to expected value analysis. As $\alpha \to \infty$, EEG approaches Rawl's maximum criterion. EEG and extended mean-absolute Gini (EEΓ) efficiency criteria are similar to EG and EΓ, respectively, with Γ(2) replaced by Γ(α). Thus, EEG and EEΓ analyses correspond very closely to ET with the exception that an *a priori* target value for the variate is not required in EEG and EEΓ. Finally, Lerman and Yitzhaki also demonstrate the following simple method for calculating Γ(α),

$$(6)\ \Gamma(\alpha) = -\alpha\,\mathrm{cov}[x,(1-F(x))^{\alpha-1}],\ \alpha > 1.$$

As indicated by Yitzhaki (1982) and further developed by Buccola and Subaei, the weaker dominance criterion leads generally to a smaller efficient set. Within the range of risk aversion, the following relations among the efficiency criteria generally hold,

Expected Value Criterion $\subseteq$ EG $\subseteq$ EEG $\subseteq$ SSD,

Expected Value Criterion $\subseteq$ ES $\subseteq$ SSD,

EG $\subseteq$ EΓ, and

EEG $\subseteq$ EEΓ.

The implication of this conceptual link among the efficiency criteria is that an investigator is able to reduce a SSD or EV efficient set by simply relaxing the dominance criteria. EEG and ET analyses provide efficiency criteria that are simple to measure empirically, and, thus, admit a search algorithm to derive efficient sets which are subsets of a SSD set. Dybvig and Ross show that SSD efficient sets are not necessarily convex; therefore, a search algorithm to derive stochastic dominant efficient sets would be difficult to construct. However, this has not precluded attempts at deriving such an algorithm (Cochran). EV is just a special case of EEG when the normality assumption is imposed.

The ease of empirically calculating EEG and the fact that EEG analysis requires no assumptions on the characteristics of the density function makes it a very attractive alternative to EV analysis. Alternatively, if *a priori* target levels of a decision variate are known, ET analysis should be considered as an efficiency criterion. The cost of employing EEG or ET analysis in attempting to reduce an efficient set is the possible increase in Type I error. However, as in SDWRF the probability of a Type I or II error in EEG and ET analyses depends on the size of the preference interval employed. Cochran provides a detailed discussion of efficiency criteria in terms of Type I and Type II errors. The above implications are empirically tested in the following sections.

APPLICATION

Problem Definition and Data Sources

Probability distributions of the decision variate, net returns, were developed with a microanalytic simulation model for soybean and wheat double-crop production in the southeastern United States (Wetzstein et al.). An intertemporal dynamic production system was simulated based on daily precipitation data for 58 weather years. Target levels for crop acreages and a machinery complement are initially specified. The model simulates the production process by generating planted acreage, based on the interaction of machinery set capacity and available work days, and harvest summary information for each year. Soybeans are planted in the spring and harvested in the fall, followed by planting wheat in the fall which is harvested the following spring. Thus, years are linked by fall wheat plantings in the previous year corresponding to the spring wheat harvest acreage in the subsequent year. The model will plant the targeted acreages each year unless planting and harvesting delays preclude the ability to achieve the targeted acreages. If initial targeted acreages of fall wheat plantings are not reached, only the actual acreage of wheat planted will be available for harvest the following spring.

The model was calibrated for a soybean and wheat double-cropping production system in the Georgia Coastal Plain. A representative soybean and wheat double-crop operation was assumed to include 600 acres with 67 percent of the acreage double-cropped. The weather data comprised 58 years of daily precipitation records from the Coastal Plain Experiment Station, Tifton, Georgia. Alternative machinery complements for eight-row equipment were modeled solely for empirical application of the various efficiency criteria and should not be considered definitive in evaluation of machinery complements. Table 1 lists the six machinery complement levels considered. Other parameters for the model, including expected value of prices and costs of materials, were estimated with standard budgeting practices.

TABLE 1. ALTERNATIVE MACHINERY COMPLEMENTS FOR PLANTING AND HARVESTING ON 600 ACRES, 67 PERCENT DOUBLE-CROP AREA, EIGHT-ROW EQUIPMENT

Machinery Complement	Tractors (135 hp)	Harvesting Systems[a]	Row Planters	Graindrills
	Numbers			
1	1	1	1	1
2	1	2	1	1
3	2	1	2	2
4	2	2	2	2
5	3	1	3	3
6	3	2	3	3

[a]One Harvesting System is composed of a combine, a trailer, and a 95-hp tractor.

Stochastic prices for soybeans and wheat were estimated with an application of the Gaussian elimination method (Clements et al.). For this procedure a variance-covariance matrix of soybean yield and prices of soybeans and wheat was estimated from Georgia state average price data and southern Georgia county yield data for 1973 through 1981 (Georgia Crop Reporting Service).

Results

Results are reported in terms of efficient set consistency among the various efficiency criteria. Pattern of membership is the pri-

TABLE 2. SUMMARY STATISTICS ASSOCIATED WITH THE EFFICIENCY CRITERIA FOR THE SIX MACHINERY DECISIONS

Statistic	Machinery Complement 1	2	3	4	5	6
Mean (μ) (Net returns per area)	\$66.74	\$48.02	\$65.14	\$45.09	\$59.60	\$39.56
Variance (σ^2)	1212.72	1052.56	763.03	779.21	702.57	726.64
Mean-Risk $[F_{\alpha}(t)]^a$						
1	24.26	29.93	19.66	26.96	20.16	27.54
1.5	173.77	202.09	99.65	163.85	101.90	168.74
2(semivariance)	1383.61	1518.96	552.67	1054.64	549.50	1092.79
5	668.00[b]	918.00[b]	39.00[b]	158.00[b]	31.00[b]	150.00[b]
Gini $(\Gamma)^a$						
1.5	9.40	8.84	7.89	7.91	7.67	7.73
2	18.47	17.33	15.32	15.48	14.83	15.04
5	40.30	36.89	30.25	30.55	28.59	28.98
$(\mu - \Gamma)^a$						
1.5	57.35	39.18	57.25	37.19	51.93	31.83
2	48.27	30.69	49.82	29.61	44.77	24.52
5	26.45	11.13	34.89	14.55	31.01	10.59
Minimum Variate	−38.90	−59.24	3.68	−16.66	4.54	−16.39

[a]Values 1 to 5 are the levels for the exponent associated with the particular summary statistic.

[b]In units of one million.

mary feature of the efficient set examined. Summary statistics associated with various efficiency criteria are reported in Table 2. The exponents for ET, EEΓ, and EEG range from 1 to 5, and the *a priori* target value for ET was set at the overall mean of the expected value levels for the six machinery decisions. The summary statistics generally vary widely within the six machinery decisions. For example, the minimum variate ranges from −59.24 to 4.54.

Table 3 reports the efficient sets associated with the various efficiency criteria. The results are consistent with theoretical expectations. FSD and SSD generally have the strongest dominance criteria and result in culling 50 percent of the machinery decisions, with decisions 1, 3, and 5 remaining in the efficient set. EV and EEΓ results correspond to FSD and SSD results, indicating in this analysis an associated level of discriminating power. Expected value, the weakest dominance criterion, reduced the efficient set down to one member, decision 1. However, the mean values for decisions 1 and 3 differ by less than three percent. Furthermore, the variance associated with decision 3 is 37 percent less than the variance for decision 1, and Γ is lower for decision 3 compared with decision 1. This indicates a possible risk preference between these two decisions. In contrast to FSD, SSD, EV and EEΓ, EEG

TABLE 3. EFFICIENT MACHINERY SET ASSOCIATED WITH SELECTED EFFICIENCY CRITERIA

Efficiency Criterion	Efficiency Set
First Degree Stochastic Dominance, FSD	1, 3, 5
Second Degree Stochastic Dominance, SSD	1, 3, 5
Stochastic Dominance With Respect to a Function, SDWRF[a]	
0.025 to ∝	5
0.019 to ∝	3, 5
Expected Value	1
Mean-Variance, EV	1, 3, 5
Extended Mean Absolute Gini, EEΓ[b]	
1.5	1, 3, 5
2 (Mean Absolute, EΓ)	1, 3, 5
5	1, 3, 5
Extended Gini Mean Difference, EEG[b]	
1.5	1
2 (Gini Mean Difference, EG)	1, 3
5	1, 3
Mean-Risk, ET[b]	
1	1, 3
1.5	1, 3
2 (Mean-Semivariance, ES)	1, 3, 5
5	1, 3, 5
Rawlsian	5

[a]Ranges listed are absolute risk aversion intervals.

[b]Values 1 to 5 are the levels for the exponent associated with the particular summary statistic.

further reduces the efficient set and discriminates between decisions 1 and 3. For values of the exponent less than or equal to 5, machinery decision 5 never enters the efficient set; and for a 1.5 exponent level, decision 3 drops out of the efficient set with decision 1 the sole remaining member.

Results for ET analysis indicate that as the value of the exponent increases, decision 5 enters the efficient set. This corresponds to greater risk aversion and is associated with SDWRF, where decisions 3 and 5 remain in the efficient set at a level of absolute risk aversion of 0.019. Decision 5 constitutes the Rawlsian efficient set, which is associated with a value for absolute risk aversion greater than 0.025 under the SDWRF criterion.

Bey and Howe note that a shortcoming of EG is its close correspondence to expected value criterion. However, in some cases this may be an advantage of EG over other criteria including SSD and EV, given the ability of EG to further reduce the efficient set. In application, EEG avoids this possible problem of correspondence between expected value and EG by providing a wide range of risk preference for the given range of the exponent.

SUMMARY AND IMPLICATIONS

The prime motivation in selecting EEΓ, EEG, and ET analysis is the simplicity of computation required in optimization procedures and the allowance for varying levels of risk preference. However, possible disadvantages include the requirement of prior target levels for ET analysis and the underestimation of risk in EG analysis.

Selley states that future developments in theory and methods of analysis should continue to generate decision rules with greater generality and wider applicability. This study indicates that in evaluating the various efficiency criteria attention should focus on EEΓ, EEG, and ET as possible directions towards greater generality. If a target value is known, then ET may be appropriate. Otherwise, EEΓ and EEG should be considered. Theoretically, EV is a special case of EEΓ which is demonstrated empirically in this paper. Furthermore, EV suffers from the inability to incorporate varying levels of risk preference. The empirical support of the theoretical relation between EEΓ and SD suggests that an EEΓ optimal search algorithm may provide a desirable starting point for developing a SD optimal search algorithm similar to Target MOTAD or lower partial moments (Atwood, Tauer).

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