Portfolio Analysis of Stocks, Bonds, and Managed Futures Using Compromise Stochastic Dominance

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INTRODUCTION

Investors, particularly large institutional investors, use the mean-variance (MV) approach of modern portfolio theory (Markowitz, 1959) to design and manage their portfolios. Many researchers use this technique to analyze the effectiveness of managed futures in diversifying equity portfolios with favorable results (Lintner, (1983), Baratz and Eresian (1986, 1990), Orr (1985, 1987), Brorsen and Irwin (1985), Irwin and Landa (1987), Fischmar and Peters (1988, 1990)), although the conclusions are not unanimous Murphy (1987), Elton, Gruber, and Rentzler (1987, 1990).

MV methodology is criticized for a number of reasons. Variance is not an intuitively appealing measure of risk because most executives and institutional investors perceive risk as the probability of not achieving a minimum level of return (Zeleny, 1982). Variance is shown to overstate the true extent of tradeoff between risk and return (Fischmar and Peters, 1988), although significantly greater risk reduction can occur than implied by the MV model (Peters, 1989). The presence of outliers can have a disproportionate effect on variance, and autocorrelation can also cause significant problems in estimation (Strahm, 1983). In addition to the difficulties inherent to variance, the MV approach requires an investor's utility function to be quadratic to determine an optimal portfolio (Hadar and Russell, 1965). In reality, most investors have no idea about the shape of their utility function (Elton and Gruber, 1987). Finally, it has been shown that some portfolios in the MV-efficient set may, in fact, be inferior to others because of a nonoverlap in the probability distribution of returns (Baumol, 1963).

Stochastic dominance (Hadar and Russell (1969), Hanoch and Levy (1965)) has been proposed as a methodology for ordering uncertain outcomes and as an alternative to MV analysis in measuring the effectiveness of investment portfolios (Levy

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and Sarnet, 1972). Its advantage is that it accounts for the entire distribution of returns instead of only the mean and variance, thereby giving a broader measure of portfolio risk and return. If some portfolios are found to be dominant over others, then no assumptions are necessary regarding investor utility functions, except that more wealth is preferred to less. However, stochastic dominance does not perform well in actual practice, where complete and distinct dominance is seldom, if ever, found.

Some attempts have been made to overcome this difficulty (Meyer, 1983); but, in so doing, the need for specifying an investor's utility function is reintroduced (Irwin and Brorsen, 1984). Other approaches utilize a concept of partial stochastic dominance (Peters, 1989), but thereby limit the measures of effectiveness to a subset of returns. This article develops the concept of compromise stochastic dominance as a practical method of applying stochastic dominance criteria without the limitations described above.

METHODOLOGY

Stochastic dominance is an intuitively appealing criterion for ranking portfolios. Its principal advantage is that it attempts to account for the entire distribution of returns, producing a multidimensional measure of portfolio performance. First degree stochastic dominance is defined by the condition:

$$F_\alpha(r) < F_\beta(r) \quad \text{for all } r \text{, provided that } F_\alpha(r) < F_\beta(r) \text{ for at least one value of return, } r, \tag{1}$$

where F_α and F_β are the cumulative probability distributions for portfolios α and β. The above condition implies that portfolio α is preferred (dominates) portfolio β if the cumulative distribution of α lies below and to the right of β, for all possible levels of return, r. Portfolios having first degree stochastic dominance provide the greatest probability of exceeding an investor's target level of return; they also provide the smallest risk of failure of achieving some minimum return. Thus, any investor, regardless of attitude toward risk, will prefer portfolios having first degree stochastic dominance (as long as more wealth is preferred to less).[1]

As mentioned above, several studies find that a pure stochastic dominance criterion does not work well in practice for stocks, bonds, or T-bills (Porter and Gaumitz, 1982), for ranking mutual funds (Meyer, 1983), for managed futures (Irwin and Brorsen, 1984), or for equity portfolios diversified with managed futures (Peters, 1989). The primary reason is that very large losses and gains are experienced occasionally in the real world by all types of investments (except perhaps T-bills), causing empirical cumulative probability distributions to overlap at one or more levels of return. Stochastic dominance is far too severe a criterion to reasonably apply to empirical distributions where this occurs.

One path of this dilemma is to use a multicriteria measure of risk that is derived from elements of stochastic dominance criteria (Colson and Zeleny, 1980). This technique makes use of a prospect-ranking vector (PRV) which includes information about three measures of performance: average return, the probability of achieving a given minimum level of return, and the probability of exceeding a given

[1]Second degree stochastic dominance has been proposed also as a criterion (Levy and Sarnet, 1972). It is defined by $\Sigma_r F_\alpha(r) = \Sigma_r F_\beta(r)$ for all r, with the strict inequality holding for at least one value of return, r. This report uses first degree dominance since first degree dominance implies second degree (Hadar and Russell, 1969).

maximum level of return. The PRV criteria are limited to cases where only the first two moments of the distribution in returns are known and where a particular type of distribution can be assumed. The PRV approach has the limitation of confining itself to three measures of performance, but is suggestive of ways in which stochastic dominance-like criteria can be practically applied.

Since clear stochastic dominance is generally impossible to find, an alternative approach is to find the best compromise—i.e., that portfolio which comes closest to satisfying the conditions for stochastic dominance. Compromise programming is proposed as a technique for identifying such a portfolio. It proceeds by first identifying the ideal solution (which is unattainable), and then uses performance measures to identify those attainable portfolios which are closest to the ideal.

The ideal portfolio is defined as one whose performance is comprised of the lower envelope of cumulative probability distributions of portfolios in the efficient MV set:

$$F^* = \operatorname*{Min}_i \{F_i(r)\} \tag{2}$$

where F^* is the stochastically dominating (first degree) portfolio for every return, r.

This ideal portfolio has the lowest probability of failure to achieve any given minimum level of return, and the maximum probability of exceeding some target level of return for any minimum or target return level specified by an investor. If first degree dominance exists among any of the efficient portfolios being considered, the ideal would coincide with it. If such dominance does not exist, then the ideal becomes the goal.

Compromise programming identifies the portfolio which comes closest to minimizing the difference in performance between itself and the ideal. A measure of this difference is defined to be:

$$L_i = \left[\sum_r p_r^s (F(\underset{i}{r}) - F^*)^s\right]^{1/s} \tag{3}$$

where:

$F(r_i)$ = probability distribution function of the ith portfolio in the efficient set,
F^* = probability distribution function of the ideal portfolio,
p_r = weight given to the rth level of return, and
s = parameter chosen to reflect the importance of the relative size of deviations from the ideal. (For $s = 1$ all deviations have equal weight; for $s > 1$ larger deviations have more weight, and vice-versa.)

The compromise stochastic dominance procedure is defined as:

$$\operatorname*{Min}_i L = \left[\sum_r p_r^s (F(r_i) - F^*)^s\right]^{1/s} \tag{4}$$

where:

$F(r_i)$ = portfolio in the MV efficient set,
$s > 1$ (small deviations have low priority),
$p = 1$ (all levels of return equally important).

DATA

Data used for this analysis are monthly returns for the period 1980–88. Stocks are represented by the S&P 500 with dividends reinvested, bonds by the Salomon

Brothers Broad Investment Grade Bond Index, and managed futures by the Managed Accounts Report Capital Weighted Index of CTA performance. See Appendix for a detailed description of managed futures data.

MEAN-VARIANCE (MV) ANALYSIS

Markowitz[1] efficient portfolio frontiers are constructed in the traditional fashion (Markowitz, 1959) with and without managed futures. The results are shown graphically in Figure 1. The efficient frontier of portfolios *including* managed futures lie substantially to the left (lower variance) and/or above (higher return for same variance) the attainable frontier with stocks and bonds alone. These results clearly indicate the benefits of using managed futures from an MV perspective, but many issues remain unanswered. Which portfolio is best? If risk is more appropriately measured as the probability of failure to achieve a given minimum level of return, then which would be the best portfolio? Would it still contain managed futures?

Table I describes in detail the MV-efficient frontiers for stocks and bonds, with and without managed futures. It is the basis upon which compromise stochastic dominance is applied. Portfolios 1–18 are derived considering stocks, bonds, and managed futures, while portfolios 19–27 include only stocks and bonds.

STOCHASTIC DOMINANCE

To test for pure stochastic dominance in the first 18 efficient portfolios of Table I, cumulative probability distributions are constructed from the empirical data for each portfolio, and are shown in Figure 2. A pair-wise comparison is made between the cumulative distributions. In each case they cross at least once, thereby ruling out first degree stochastic dominance.

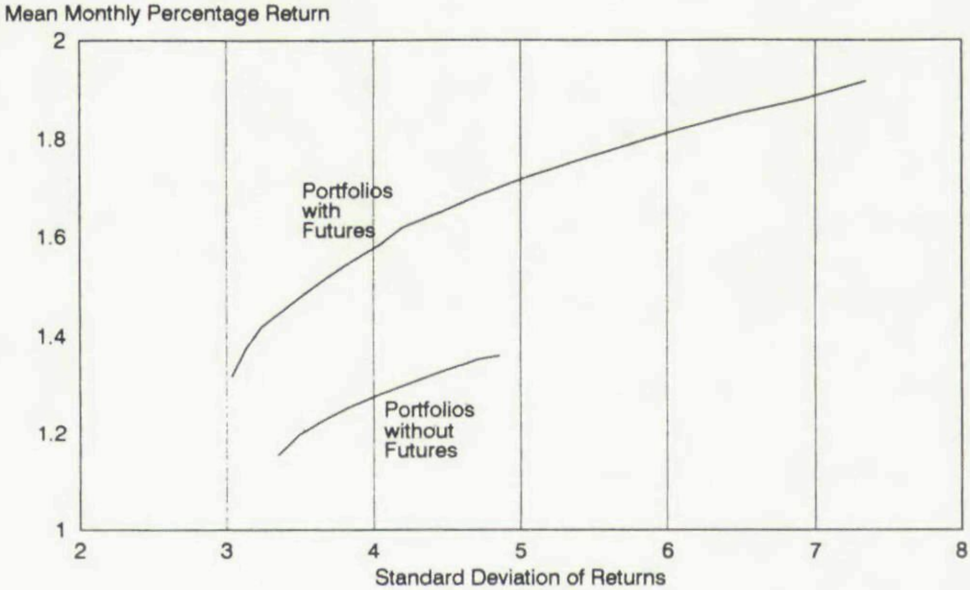

Figure 1
Portfolios with and without futures

Table I
MV-EFFICIENT FRONTIERS

Portfolio	Stocks (%)	Bonds (%)	Managed Futures (%)	Average Mo. Return (%)	Monthly Std. Dev. (%)	Minimum Mo. Return (%)
1	28.3	49.5	22.2	1.32	3.03	−4.82
2	31.2	42.9	25.9	1.36	3.10	−4.72
3	34.5	35.6	29.9	1.41	3.23	−4.60
4	36.7	30.5	32.8	1.44	3.35	−4.62
5	38.9	25.4	35.7	1.48	3.49	−5.09
6	41.8	18.9	39.3	1.52	3.69	−5.71
7	43.4	15.2	41.4	1.54	3.81	−6.06
8	46.3	8.6	45.1	1.59	4.05	−6.68
9	47.8	5.1	47.0	1.61	4.18	−7.00
10	48.2	0	51.8	1.65	4.46	−6.96
11	42.2	0	57.8	1.68	4.71	−7.20
12	36.2	0	63.8	1.72	5.00	−7.76
13	30.1	0	69.9	1.75	5.33	−8.33
14	24.1	0	75.9	1.78	5.69	−8.89
15	18.1	0	81.9	1.82	6.08	−9.45
16	12.0	0	88.0	1.85	6.49	−10.03
17	5.9	0	94.0	1.88	6.91	−10.59
18	0	0	100.0	1.92	7.34	−11.15
19	38.9	61.0	0	1.16	3.35	−6.14
20	51.4	48.6	0	1.20	3.49	−9.29
21	61.6	38.4	0	1.23	3.69	−11.86
22	66.8	33.2	0	1.25	3.81	−13.17
23	75.8	24.2	0	1.28	4.05	−15.43
24	80.3	19.7	0	1.30	4.18	−16.57
25	89.0	11.0	0	1.33	4.46	−18.76
26	96.3	3.7	0	1.35	4.71	−20.60
27	100.0	0	0	1.37	4.85	−21.53

The reason for this inability of the stochastic dominance criteria to establish any preferred ordering of the efficient set can be seen in Table I. In general, as the mean return of a portfolio increases, the lowest return for that portfolio becomes more extreme. The behavior of these extreme points in the cumulative distribution makes any single dominance criterion incapable of ordering the efficient set. Stochastic dominance (first degree), as a criterion for ordering efficient portfolios, is hampered by the fact that extreme returns, however small their probability, can cause an overlap in the cumulative distributions.

COMPROMISE STOCHASTIC DOMINANCE

Compromise stochastic dominance identifies the portfolio that comes closest to the ideal. The ideal portfolio is defined as the lower envelope of cumulative probability distribution functions of all portfolios in the efficient frontier, as is shown in Figure 2.

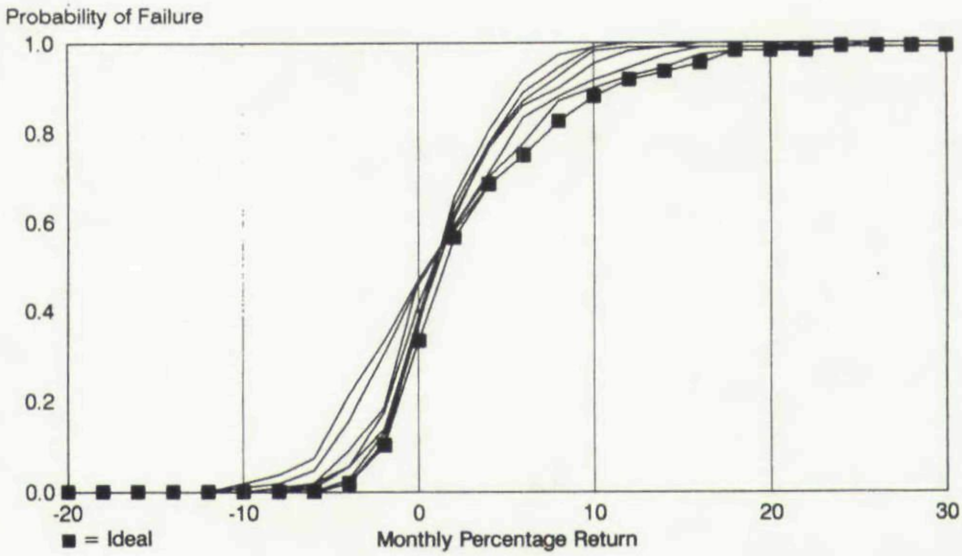

Figure 2
Cumulative Distributions—Actual and Ideal Portfolios

Monthly returns in the efficient portfolios vary between the extremes of -20.8% to $+34.4\%$. This range is arbitrarily divided into intervals of .4%, yielding 139 separate points of comparison between the ideal and actual portfolios considered. The procedure defined by eq. (4) is applied with $p = 1$ and $s > 1$. The justification for setting $p = 1$ is that, in the absence of any other information about the decision-maker, first degree stochastic dominance regards every level of return as equally important. (Potentially, this technique could be tailored to the preferences of the decision-maker by adjusting the values of p). Regarding s, large deviations are considered usually to be more critical than small deviations. Therefore, $s > 1$ is used for the analysis. Table II shows the values of L for the portfolios for varying levels of s. Portfolios 10 and 11 represent the best compromise between the ideal and actual. These portfolios contain *no bonds,* between 42% and 48% stocks, and 52% to 58% managed futures.

Figure 3 illustrates the cumulative distributions of portfolio 10 compared to the ideal. According to the stated definition, no other portfolio is better at approaching the ideal.

The compromise stochastic dominance procedure is applied also to the stock- and bond-efficient frontier. The results are presented in Table III. One can now further appreciate the benefits of the stochastic dominance approach by the insight it brings to the tradeoff between risk and reward. Portfolio 27 (containing all stocks) is the best compromise solution from this efficient set; but it is inferior to the best compromise from the set containing managed futures, portfolio 10 (48.2% stocks, 51.8% managed futures). However, note that portfolios 1–6 (using between 22% and 39% managed futures) are inferior to portfolio 27 (all stocks). This result is different from what one would conclude from the MV approach (shown in Table I) where portfolios 1–6 clearly are preferable to portfolio 27.

The approach shown herein indicates the possibility that under some realistic circumstances (e.g., $p = 1$, $s > 0$), some *inefficient* portfolios may be a better

Table II
VALUES OF L FOR THE STOCK, BOND AND MANAGED FUTURES MV-EFFICIENT FRONTIER

	L		
Portfolio	$S = 2$	$S = 10$	$S = \infty$
1	.7353	.2041	.1753
2	.7026	.1929	.1667
3	.6832	.1853	.1574
4	.6557	.1731	.1481
5	.6248	.1644	.1389
6	.6082	.1572	.1296
7	.5869	.1526	.1296
8	.5634	.1471	.1296
9	.5526	.1463	.1296
10	.5283	.1270*	.1111*
11	.5231*	.1358	.1204
12	.5358	.1643	.1574
13	.5478	.1913	.1759
14	.5697	.2071	.1819
15	.6082	.2324	.2130
16	.6541	.2434	.2222
17	.6991	.2520	.2222
18	.7638	.2704	.2315

* = Minimum L.

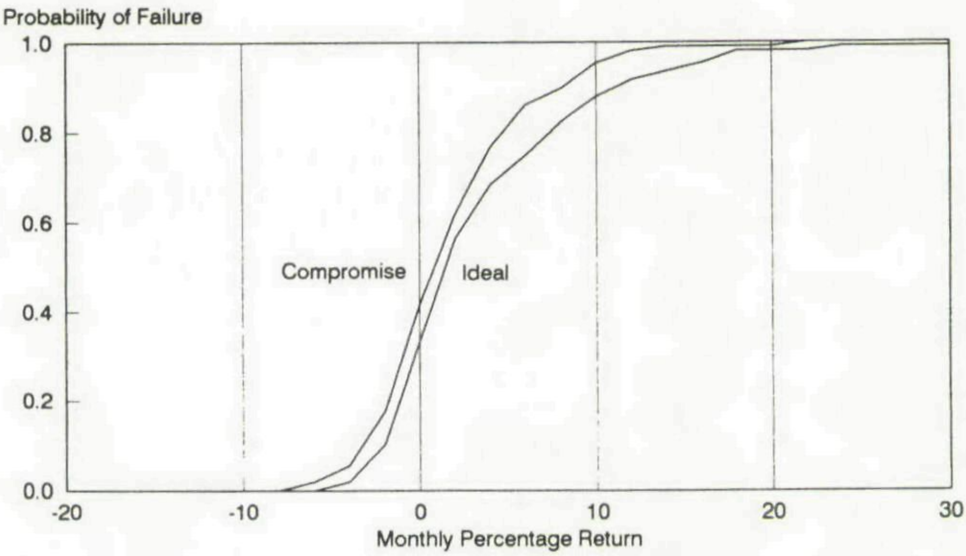

Figure 3
Cumulative Distributions—Compromise and Ideal Portfolios

Table III
VALUES OF L FOR THE STOCK AND BOND MV-EFFICIENT FRONTIER

Portfolio	L		
	$S = 2$	$S = 10$	$S = \infty$
19	.7422	.2115	.1852
20	.7230	.2022	.1852
21	.6904	.1826	.1481
22	.6774	.1806	.1481
23	.6470	.1715	.1481
24	.6341	.1687	.1389
25	.6068	.1626	.1389
26	.5926	.1573	.1389
27	.5817*	.1529*	.1296*

* = Minimum L.

compromise alternative than portfolios on the efficient frontier for the assets considered here.

Another conclusion, which is different from others using an MV approach, is that the stochastic dominance framework reveals the possibility that a candidate asset class for diversification may have a minimum threshold allocation before improved performance can be realized for the portfolio. For example, portfolio 21 (approximately 62% stocks, 38% bonds—an optimal portfolio based on returns since 1926 (Elton, Gruber, and Rentzler, 1987) dominates portfolios 1–4 (stocks, bonds, and managed futures) until the managed futures component reaches approximately 35%. Other calculations done by the authors (not shown here) indicate that approximately 20% managed futures are needed as a minimum threshold to dominate the worst of stock-bond portfolios. The MV approach, on the other hand, dictates only that the ratio of excess return to variance of the candidate asset class for diversification exceed the same ratio for the portfolio multiplied by the correlation between the two (Elton, Gruber, and Rentzler, 1987). There is no minimum threshold requirement in the MV approach.

Table IV compares all 27 portfolios with respect to various measures of risk.

In contrast to the Markowitz criteria, not all the portfolios that exclude futures are dominated by portfolios that include futures. The column labeled $s = \infty$ reveals that the "nonfutures" portfolios 21–27 perform reasonably well when compared with portfolios 1–4 and 12–18.

The reason for this result can be seen in the columns that give the probability of returns below 0% and 0.4%. Examination of those columns reveals that the nonfutures portfolios perform well in terms of these relatively limited set of criteria. In fact, if one adopts the single criterion of minimizing the probability of returns below 0%, the nonfutures portfolio 21 becomes optimal. And, if one adopts the single criterion of minimizing the probability of returns below 0.4%, "nonfutures portfolios" 21–24 are the preferred choices to portfolios 1–18 with managed futures.

The problem with such single-dimension criteria can be understood by examining of the last column in Table IV. Although portfolios 21–24 minimize the probability of missing a very small return, they are inferior in their ability to prevent larger losses. For example: from the last column of Table IV, it is evident that portfolio 10

Table IV

Portfolio	Stocks (%)	Bonds (%)	Managed Futures (%)	L for $S = \infty$	Prob. of Return Less Than: 0%	.4%	−2.8%
1	28.3	49.5	22.2	.1753	.3704	.4722	.0833
2	31.2	42.9	25.9	.1667	.3704	.4537	.0648
3	34.5	35.6	29.9	.1574	.3796	.4352	.0741
4	36.7	30.5	32.8	.1481	.3889	.4537	.0741
5	38.9	25.4	35.7	.1389	.3704	.4537	.0833
6	41.8	18.9	39.3	.1296	.3796	.4722	.0648
7	43.4	15.2	41.4	.1296	.3796	.4537	.0741
8	46.3	8.6	45.1	.1296	.3889	.4630	.0741
9	47.8	5.1	47.0	.1296	.3981	.4630	.0741
10	48.2	0	51.8	.1111	.4167	.4815	.0926
11	42.2	0	57.8	.1204	.4352	.4815	.1111
12	36.2	0	63.8	.1574	.4444	.5185	.1389
13	30.1	0	69.9	.1759	.4722	.5278	.1389
14	24.1	0	75.9	.1819	.4537	.5093	.1481
15	18.1	0	81.9	.2130	.4630	.5093	.2037
16	12.0	0	88.0	.2222	.4630	.5093	.2593
17	5.9	0	94.0	.2222	.4722	.5000	.2778
18	0	0	100.0	.2315	.4722	.5000	.2870
19	38.9	61.0	0	.1852	.3704	.4259	.1111
20	51.4	48.6	0	.1852	.3519	.4167	.1204
21	61.6	38.4	0	.1481	.3333	.3889	.1204
22	66.8	33.2	0	.1481	.3426	.3889	.1204
23	75.8	24.2	0	.1481	.3519	.3889	.1296
24	80.3	19.7	0	.1389	.3519	.3889	.1389
25	89.0	11.0	0	.1389	.3704	.3981	.1389
26	96.3	3.7	0	.1389	.3611	.3981	.1574
27	100.0	0	0	.1296	.3611	.4167	.1574

yields a .0926 chance of losing 2.8% or more. In contrast, portfolio 21 increases that risk to .1204, an increase of 30% compared with portfolio 10.

Similarly, the "nonfutures" portfolios perform poorly at the upper ends of the return distribution. For example: The probability of a return in excess of 8% is .037 for portfolio 21 and .1019 for portfolio 10. (This calculation is not presented in Table IV.) Thus, the futures portfolio 10 increases the chance of returns in excess of 8% by 175% compared with portfolio 21.

Generally, the "nonfutures" portfolios only provide better performance over a very limited range of the return distribution. "Nonfutures" portfolios 20–25 generally perform better than the "futures" portfolios over the range from 0–2% return, but are dominated by the "futures" portfolios at every other point in the distribution of returns. Portfolios that include futures do a better job of maximizing the probability of achieving any given target return and minimizing the probability of loss, except for the narrow range between 0–2%.

In summary, the evidence provided suggests that the proper way to evaluate portfolios is through a methodology that takes into account all possible levels of return. Risk is inherently a multidimensional concept that should be evaluated with multicriteria decision techniques. Since the risk of large losses as well as the failure to achieve large returns are as significant in the risk calculus as failure to achieve a single target such as the risk-free return, a multidimensional method, one that utilizes the techniques presented in this report, appears to be warranted.

A limitation of this technique is that there are an infinite number of possible portfolios, whereas only a discrete subset of empirical distributions can be used to define the ideal and compromise portfolios. However, this limitation is not unique to compromise dominance; stochastic dominance itself operates in the same way and requires an investor to partition the infinite set into a manageable and practical subset of alternative portfolios.

CONCLUSIONS

Compromise dominance provides a method for selecting from among a set of portfolios one that comes closest to dominating the others according to first degree stochastic dominance criteria. It allows the ordering of portfolios when complete stochastic dominance is impossible, as it usually is in real-world applications. It offers an alternative to other stochastic dominance ranking techniques that use modifications which often damage the nearly assumption-free nature of the original criteria.

Portfolios consisting of stocks and/or bonds and/or managed futures are analyzed based on monthly returns for the period 1980–88. Portfolios consisting of approximately one-half stocks and one-half managed futures dominate all other portfolios, based on the compromise dominance criteria. It is found that minimum thresholds of managed futures are needed to produce beneficial results, in contrast to the conclusions of modern portfolio theory, which does not imply thresholds. The analysis also shows that, under some realistic circumstances, inefficient Markowitz portfolios offer a better compromise alternative than portfolios on the efficient frontier.

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Appendix

DATA SOURCE FOR MANAGED FUTURES RETURNS

The data used for performance of managed futures is the Managed Accounts Report (MAR) Commodity Trading Advisor (CTA) Index (dollar weighted), compiled by Managed Accounts Report, Inc. of Columbia, MD. The MAR CTA Index consists of equity-weighted performance of a representative group of CTAs monitored by Managed Accounts Report, Inc. Returns for each advisor are subject to audit by the National Futures Association (NFA) and Commodity Futures Trading Commission (CFTC). In 1988, the Index consisted of returns from 25 advisors, which at that time represented approximately 80% of all the equity managed by advisors tracked by Managed Accounts Report. Advisors are selected on the basis of equity under management in the preceeding year, and are kept in the Index for the following year regardless of their performance. Testing done by Managed Accounts Report, Inc. indicates no significant difference between performance of the Index and its universe.