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The risk level discriminatory power of mutual fund investment objectives: Additional evidence☆

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Abstract

We reexamine the information content of mutual fund investment objectives to learn whether investors can use them to infer risk. For investment objectives to properly convey risk, risk must be heterogeneous between investment objective groups and homogeneous within them. The present study differs from earlier work in two important ways: (1) it reaches a generally different conclusion about within-objective class fund risk, and (2) it is being done against a backdrop of industry-wide incentive compensation structures that rely on these classifications as proxies for fund volatility. Empirical testing suggests that risk is heterogeneous within groups.

JEL classification: G11; G12

Keywords: Mutual fund classifications; Mutual fund investment objectives; Mutual fund risk

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1. Introduction

This paper revisits the issue of mutual fund risk from the perspective of both domestic and globally diversified investors. The riskiness of mutual funds is a topical issue considering the Security and Exchange Commissions (SEC) recent announcement that the incoming chief economist was charged with finding a way to properly convey risk to investors.[1] This is a priori evidence that the SEC believes that there are some difficulties in this area. The SEC's concerns appear to be well founded. Brown et al. (1996) show that portfolio managers of winning and losing growth mutual fund portfolios manipulate risk, as measured by standard deviation of monthly returns, differently due to compensation incentives.[2] Orphanides (1996) finds similar results using both growth and growth and income fund classifications.

Investors are likely to be concerned with the average systematic risk of a fund over their investment horizon. Therefore, the recent findings by Brown et al. (1996) that winning and losing managers manipulate total variability differently over the next two quarters does not necessarily provide insight about risk to long term investors. Further examination of risk is important since Brown, Harlow, and Starks' theory is not necessarily extendable into longer horizons, particularly under efficient monitoring. If monitoring is efficient, and funds are constrained by investment objectives, managers may alter risk, but only within a narrow band (unless shareholders approve a change in the investment objective of the fund). The result may be that funds do alter risk periodically, but it may be that fund managers only increase or decrease risk within a narrow band around a given level of systematic risk determined by the funds investment objectives. In other words, portfolio composition is constrained unless monitoring is ineffective (particularly in the longer term).

Further study of this issue is particularly important since the results of Brown et al. (1996) stand in stark contrast to previous research on the importance of investment objectives in conveying risk if these risk differences are of such magnitude that investors cannot use investment objectives to compare funds (e.g., Sharpe, 1966; Klemkosky, 1976; Bogle, 1991). Therefore, these new results have substantial importance to the mutual fund industry, investors, and regulators. Particularly important is the effect on investors since many studies (e.g., Capon et al., 1996; Goetzmann et al., 1992; Sirri and Tufano, 1992) suggest that past performance affects fund selection and that funds with higher returns elicit more net new money inflows. The decision to invest in funds with the highest

[1] *The Wall Street Journal*, June 14, 1995.

[2] Portfolio manager response to economic incentives has been studied intensively by Cohen and Starks (1988), Golec (1992), Grinblatt and Titman (1987,1989a), Grinold and Rudd (1987), Kritzmam (1987) and Starks (1987).

return may be sub-optimal if these high returns are accompanied by high risk as theory would suggest.

We suggest that this may be the case and that recent findings of risk alteration results are pervasive. These intertemporal risk shifts may result in significant systematic risk differences between funds within any investment objective classification. Further, these within-objective risk differences may be independent of the selected reference portfolio. For investment objectives to properly convey risk they must be: (i) systematically related to a quantitative measure of risk such as beta or volatility, (ii) homogeneous within investment objective groups and (iii) heterogeneous between them. If investment objectives properly convey risk, comparing funds within an investment objective group is logical and proper. However, Christopherson (1995) and Bowen and Statman (1997) find that if investment objectives do not properly convey risk, comparison of fund returns is improper.

The present study differs from earlier work in two important ways: (1) it reaches a generally different conclusion about within-objective class fund risk, and (2) it is being done against a backdrop of industry-wide incentive compensation structures that rely on these classifications as proxies for fund volatility.

The paper is organized as follows. Section 2 provides further motivation and reviews relevant theoretical and empirical studies. The hypotheses to be tested, data sources used, and methodologies employed are detailed in Section 3. Section 4 provides empirical evidence and Section 5 concludes.

2. Mutual fund investment objectives and risk

2.1. Investment objectives as a surrogate for risk

Past research suggests that investment objectives provide a good surrogate for risk. Sharpe (1966) reports that mutual funds select a risk class and then invite investors with similar risk preferences to invest. He characterizes this as a general degree of planned portfolio risk but stresses that a fund must remain in the same risk class so that investors may arrange portfolio holdings.

Bogle (1970) examines whether the risk-return relationship of a mutual fund is consistent over time and finds that returns increase with the riskiness of the investment objective and with the standard deviation of returns. He also finds that risk is relatively constant within groups. Carlson (1970) also finds that returns increase with risk and that the risk-return relationship is linear. McDonald (1974) examines the relation between stated investment objectives, risk, and return. He finds that the stated objectives are positively related to variance and beta, and that the investment objective explains about as much variability as does systematic or total risk.

The most conclusive statistical test on the risk conveyance of investment objectives is developed by Klemkosky (1976). He extends previous research by using Weisenberger classifications and monthly data over a ten-year period to conduct statistical testing on whether investment objectives convey risk. Specifically, he tests whether investment objective classifications result in groupings that have homogeneous within-group and heterogeneous between-group risk. This is vital since it would enable investors to select funds based on raw returns.[3] Klemkosky finds that there is a consistent relationship between risk and investment objective classification, and that risk is relatively constant over time. Therefore, he concludes that the 'Weisenberger classifications are associated with market risk classes which are statistically independent' and that 'there has been little change in the relative homogeneity of fund β coefficients within each objective classification'. This rather convincing body of evidence may lead rational investors to believe that the security market line is divided into risk segments, and that each segment is occupied by mutual funds within the same investment objective class.

Starks (1987) provides theoretical justification for the empirical evidence by examining the impact that compensation contracts have on the investment decisions of portfolio managers. By assuming that investors are primarily concerned with the return and variance of return, she uses a principle-agent framework where both the principal and agent are utility maximizers. She concludes that with symmetric information, compensation contracts will cause portfolio managers to choose the investors' optimal risk level and that risk can be proxied by the investment objective of the fund.

Finally, the Securities and Exchange Commission (SEC) requires that mutual funds disclose risk to potential investors through the prospectus. The prospectus outlines the objectives of the fund and investment constraints placed upon the portfolio manager. These investment objectives must be adhered to and may only be changed with approval of the shareholders by a majority vote. Therefore, in a world of perfect monitoring, mutual funds would be required to remain within a stated risk class.

2.2. *Competition, compensation contracting, and imperfect monitoring effects on risk*

If information asymmetry about risk and imperfect monitoring exist, problems arise. Investors may be inclined to monitor returns since they are easily observable and ignore potential risk differences. This would be logical if the investors are convinced that risk is homogeneous within investment objective classes, as reported by Klemkosky (1976).

[3] Under the assumption that risk is equal, the law-of-one price should prevail. Therefore, investors need merely to select funds that have statistically higher returns.

If investors believe in the capital asset pricing model (CAPM) and the efficient market hypothesis (EMH), they would likely believe that differences in returns are either driven by risk differences or due to chance. This is because the returns on a portfolio are expected to equal the risk- free rate plus beta times the market risk premium, or $E(R_{\mathrm{p}}) = R_{\mathrm{F}} + \beta_{\mathrm{p}}[E(R_{\mathrm{m}}) - R_{\mathrm{F}}]$. Here, performance information would have no relative effect on the inflow of new money into a particular fund since differences in ex ante portfolio returns would be attributed to differences in β of the portfolios since $E(R_{\mathrm{p}a}) - E(R_{\mathrm{p}b}) = \beta_{\mathrm{p}a} - \beta_{\mathrm{p}b}[E(R_{\mathrm{m}}) - R_{\mathrm{F}}]$. However, if investors believe that superior management can garner superior ex post returns they would likely increase investments in those funds believed to be the better performers. This is because the above equation can be adapted to be $R_{\mathrm{p}} - R_{\mathrm{F}} = \alpha + \beta_{\mathrm{p}}(R_{\mathrm{m}} - R_{\mathrm{F}}) + \varepsilon_{\mathrm{p}}$. Here, α may be believed to be positive due to either superior stock selection or timing ability on the part of the portfolio manager(s) and ε_{p} is a mean-zero random error term.[4] Now, it is possible for $R_{\mathrm{p}a} > R_{\mathrm{p}b}$ when $\beta_{\mathrm{p}a} = \beta_{\mathrm{p}b}$ if $\alpha_{\mathrm{p}a} > \alpha_{\mathrm{p}b}$.

Ippolito (1992), Sirri and Tufano (1992) and Chevalier and Ellison (1995), find that fund flows to mutual funds are positively related to performance results. Better performing funds, in terms of rank or raw returns, receive greater inflows of new money. Since α requires computation, it is logical for investors to prefer raw return measures. The belief that differential management talent exists may cause investors to perceive that the return generation process is really $R_{\mathrm{p}} = R_{\mathrm{F}} + \delta + \beta_{\mathrm{p}}(R_{\mathrm{m}} - R_{\mathrm{F}}) + \varepsilon_{\mathrm{p}}$, where δ reflects management skill. If δ is positive, the portfolio manager is successful at beating the index. If δ is negative, the manager underperforms the index. However, it is not necessary for δ to be positive to elicit higher fund flows. A sufficient condition for fund A to elicit higher inflows than fund B is that $\delta_a > \delta_b$, even though both may be negative due to transaction costs. This is because it is possible for $R_{\mathrm{p}a} > R_{\mathrm{p}b}$ when $\beta_{\mathrm{p}a} = \beta_{\mathrm{p}b}$ if $\delta_{\mathrm{p}a} > \delta_{\mathrm{p}b}$.

Portfolio managers believing that investors will monitor returns and disregard potential risk differences may be compelled to take on additional risk to bolster returns, thereby, making their fund appear superior to the competition. This is because $R_{\mathrm{p}a} > R_{\mathrm{p}b}$ when $\beta_{\mathrm{p}a} > \beta_{\mathrm{p}b}$ if $\delta_{\mathrm{p}a} = \delta_{\mathrm{p}b}$. This creates an agency problem for a manager compensated on a percent of assets under management basis since the manager, attempting to maximize compensation, will attempt to maximize assets under management. Two avenues exist to increase managed assets. First, the manager may try to earn a high return to grow the current assets under management.[5] Since the value of assets under management (a) at

[4] While no known theory allows for the expected risk-adjusted return to be positive, this could explain the findings that funds with better past performance elicit more net new money inflows (e.g., Capon et al., 1996; Goetzmann et al. (1992); Sirri and Tufano, 1992).

[5] We will ignore possible changes in assets under management due to redemptions or new investments for the time being.

time $t+1$ equals the (a) at time t times $(1+r)$, where r is the realized return over the period, increasing r increases assets under management (a). The other option is to increase net new money flowing into the fund. Net new money can be defined as the new money flowing into the fund minus the old money flowing out of the fund. Now assume that informed investors realize that past research suggests that investment objectives convey risk. Therefore, investors only compare raw returns on funds within the investment objective that satisfies their desired level of risk. Investors characterizing the world in this manner are likely to invest more heavily in funds that have higher raw returns, believing that higher raw returns translate into higher risk-adjusted returns. As shown above, this may be because it is possible for $R_{pa} > R_{pb}$ when $\beta_{pa} = \beta_{pb}$ if $\delta_{pa} > \delta_{pb}$. They may also extract monies from funds with lower raw returns and move the money into funds with higher raw returns.[6] This investment of net new money causes assets under management to grow since the value of assets (a) at time $t+1$ are equal to (a) plus net inflows of invested funds during the period.

Raw returns affect portfolio managers in two ways here. First, high raw returns allow the manager to grow the assets under management (a). Secondly, high raw returns may result in larger net new money inflows. In both cases, assets under management (a) grow, and so does the portfolio managers' compensation.

However, if raw returns and risk are linearly related, increasing raw returns requires increasing risk. While SEC regulations prohibit changing the investment objectives of the fund and require disclosure of the portfolio periodically, managers can alter risk unobserved under imperfect monitoring. Therefore, it is possible for the portfolio manager to increase risk and raw returns since $R_{pa} > R_{pb}$ when $\beta_{pa} > \beta_{pb}$ if $\alpha_{pa} = \alpha_{pb}$. So if monitoring of risk is imperfect, portfolio managers will have an incentive to alter risk within limits that they believe that will remain unobservable.[7]

2.3. Recent related supporting evidence

While there is abundant early evidence that investment objective classes provide a surrogate for risk that is homogeneous within each investment

[6] Goetzmann and Peles (1997) find that outflows of invested monies may be less sensitive than inflows since investors may not want to admit a mistake or risk making another one.

[7] Investors may clearly understand this agency problem however, their response to it would depend on their opinion about the risk level discriminatory power of investment objectives and their perception of the ability of SEC regulations and monitoring to constrain portfolio managers' behavior. If investors believe that monitoring is ineffective and that substantial risk differences exist within investment objectives groups, they would have no reason to increase investments in funds generating high returns (here, investors may believe that high returns are explained by high risk). However, if investors believe that investment objectives explain risk, and believe that the SEC ensures that portfolio managers are constrained to a range of risk, they would be inclined to invest more heavily in funds that produce higher returns.

objective class, there is also some later evidence suggesting that this may no longer be the case. First, the differences in returns between the top performing and bottom performing funds reported in the *Wall Street Journal* for each investment objective class appear to be too large to be explained by chance. Second, Brown et al. (1996) and Orphanides (1996) find that mutual fund managers have an incentive to alter the risk of their portfolios because their compensation is tied to the relative performance of their fund. Therefore, losing funds tend to increase risk to regain relative performance. This recent body of evidence differs from previous research and compels us to ask whether investment objectives continue to convey risk properly. If portfolio variances differ significantly, betas may differ also under the Capital Asset Pricing Model (CAPM) since $\beta_{\mathrm{p}} = \rho(\sigma_{\mathrm{p}}/\sigma_{\mathrm{m}})$, where ρ is the correlation between the portfolio and the market and σ_{p} and σ_{m} are the portfolio and market variabilities, respectively.

3. Empirical examination

3.1. Data

Our sample consists of open-end mutual funds continuously in operation during the period September 1981 through September 1994 produced by CDA Investment Technology, Incorporated.[8] To be consistent with the methodology employed by other researchers,[9] we sort the funds by the eight CDA investment objectives at the end of the period. Final screening eliminates country and regional specific funds to ensure homogeneity of the international fund sample.

Screening results in a total sample of 377 funds, consisting of 43 aggressive growth (AG), 112 growth (G), 66 growth and income (GI), 36 balanced (B), 16 international (IN), 8 precious metal (ME), 66 bond and preferred stock (BP), and 30 municipal bond (MB) funds. These investment objective classes are typically

[8] The *CDA Mutual Fund Hypo* program produced by CDA Investment Technology, was used to obtain data. Two constraints drive our sample period. First, is the necessity to examine funds that can be sold to investors. Therefore, extinct funds are excluded. Secondly, sufficient performance history was required to provide meaningful statistical power for our tests. The exclusion of newer funds causes ‘omission’ bias. Omission bias would cause our significance tests for individual funds to be understated since the ANOVA methodology tests for differences between funds. Therefore, the results of this paper are stronger than reported. Also, studies such as Brown et al. (1992) show survivorship bias exists when extinct mutual funds are excluded when studying performance. Malkiel (1995) suggests that fund disappearance may be caused by funds taking big bets and losing. If disappearance is related to a large alteration in risk that backfired, eliminating extinct funds would bias against finding risk differences.

[9] This is consistent with the works of Bogle (1970,1991), Carlson (1970), McDonald (1974), Klemkosky (1976), Ippolito (1989), and Grinblatt and Titman (1989a,b,1993).

characterized as indicated in Appendix A. As a test of robustness, the Lipper and Brown and Goetzmann (1997) classifications are also used.

Return data for the S&P 500 Index, Dow Jones Industrial Average (DJIA), Shearson Lehman Municipal Bond Index, Shearson Lehman Government and Corporate Bond Index, and the risk-free proxy (T-bill return) is also from CDA. Additionally, we use the Center of Research in Security Prices (CRSP) return data for the CRSP equally weighted (EW) and value weighted (VW) indices. Return data for the Morgan Stanley Capital International Perspective Index (MSCI) is also used to examine robustness of our results.

3.2. Computation of returns

Holding period returns are computed using the change in wealth over the holding period, assuming reinvestment of all dividends and realized capital gains. The returns are calculated as

$$R_{it} = \frac{NAV_{it} + D_{it} + CG_{it} - NAV_{it-1}}{NAV_{it-1}} \tag{1}$$

where R_{it} is the return on fund i during period t, NAV_{it} is the net asset value of fund i at time t, D_{it} is the dividend distribution of fund i during holding period t, CG_{it} is the capital gain distribution of fund i during holding period t, and NAV_{it-1} is the net asset value of fund i at time $t-1$.

3.3. Determination of systematic risk

Systematic risk is computed by using the Jensen (1968) market model. The model used is:

$$R_{\mathrm{mf}i} - R_{\mathrm{f}} = \alpha + \beta(R_{\mathrm{M}} - R_{\mathrm{f}}) + \varepsilon \tag{2}$$

where $R_{\mathrm{mf}i}$ is the return on mutual fund i, R_{f} is the return on the risk-free asset (T-bill return), and R_{M} is the return on the various selected market proxies. β measures the systematic risk for each mutual fund from the perspective of an investor that holds a portfolio identical to the selected market proxy.[10] If the investment objective classification conveys risk, the β's for funds within each investment objective classification should not differ significantly from one

[10] For investment objectives to properly convey risk, target betas should be a function of the selected investment objective. A random sample of these betas is expected to be normally distributed around the point estimate determined by that objective. We use the ANOVA methodology to compare the factor level means of estimated systematic risk for funds receiving different treatments (managers), under the assumption that these managers face similar portfolio composition constraints that cause the variance of betas to be equal. We assume that this is the case because monitoring is intended to prevent portfolio managers from altering risk beyond certain limits.

another for a given index, although they may differ for different indices.[11] Additionally, if investment objective classes effectively discriminate between different risk classes, there should be a statistically significant difference between the average risk, β, of funds in different risk classes.

4. The information content of risk

4.1. The relationship between risk and return

Extant evidence suggests that risk increases with the movement from municipal bond funds through bond and preferred stock, balanced, growth and income, growth, to aggressive growth; effectively partitioning the security market line into segments, each associated with a particular investment objective class. Table 1 (Panel A) shows that the risk of domestic equity funds fit the pattern expected; Municipal Bond (MB) funds are the least risky and risk increases with movement toward Aggressive Growth (AG). Consistent with theory, the estimated risk depends on the selected benchmark since beta is a function portfolio variance, the variance of the market proxy, and the correlation between the portfolio and the market proxy.

For investment objectives to convey risk, objectives must be able to discriminate between the systematic risk of funds in general. Table 1 (Panel B) provides the results of a One-way ANOVA test of the null hypothesis that the risk of all funds is equal. Clearly, significant differences in risk exist, despite the selected reference portfolio. The null hypothesis of equal risk is rejected at the 0.01 significance level for each of the five indices for each of the three sample periods (the entire period (9/81–9/94), and two subperiods formed by dividing the sample period in two equal parts (9/81–3/88 and 3/88–9/94). These results are consistent with the findings of Reints and Vandenberg (1973) and Klemkosky (1976).

While the focus of this investigation is on risk, it is useful to examine risk-adjusted returns within each of the investment objective classes to ascertain whether the increase in risk is rewarded with significantly higher risk-adjusted returns. Results in Table 2 suggest that few investment objective groups exhibit statistically significant performance. Additionally, some of the excess performance is benchmark related. Interestingly, the most risky funds, aggressive growth, exhibit significantly negative risk-adjusted returns while municipal bond, and bond and preferred stock funds exhibit significantly positive risk-adjusted returns. This may well be benchmark related since Brown and Brown (1987) show that equity indices are poor benchmarks for bond portfolios. While

[11] Brown and Brown (1987), Lehmann and Modest (1987), and Roll (1978) discuss the importance of the selected market proxy.

Table 1
Average systematic risk and risk homogeneity among investment objective classes

Panel A

Classification	No. of funds	Average β from 9/81–9/94 by index				
		β_{DJ}	β_{SP}	β_{EW}	β_{VW}	β_{W}
Aggressive growth (*AG*)	43	1.100	1.152	1.110	1.193	0.889
Growth (*G*)	112	0.924	0.967	0.892	1.000	0.755
Growth and Income (*GI*)	66	0.736	0.768	0.691	0.790	0.606
Balanced (*B*)	36	0.595	0.625	0.560	0.644	0.494
Bond and preferred stock (*BP*)	66	0.188	0.205	0.194	0.214	0.170
Municipal bond (*MB*)	30	0.175	0.190	0.148	0.190	0.140
International (*IN*)	16	0.783	0.782	0.734	0.790	0.885
Metal (*ME*)	8	0.480	0.390	0.093	0.414	0.769
Total	377					

Panel B

Period	F_{DJ}	F_{SP}	F_{EW}	F_{VW}	F_{W}
9/81–3/88	283.420[a]	290.120[a]	281.036[a]	287.123[a]	316.464[a]
3/88–9/94	340.555[a]	337.812[a]	260.776[a]	366.168[a]	288.753[a]
9/81–9/94	348.635[a]	366.413[a]	324.975[a]	360.129[a]	392.620[a]

[a]Indicates significance at the 0.01 level.
Note: Panel A column one provides the CDA investment objective. Column two is the number of funds comprising the sample, and columns three through seven present the estimated systematic risk for investors. β_{DJ} is estimated using the DJIA as a market proxy, β_{SP} is estimated using the S&P 500 as a market proxy, β_{EW} is estimated using the CRSP EW index as a market proxy, β_{VW} is estimated using the CRSP VW index as a market proxy, and β_{W} is the systematic risk for globally diversified investors estimated using the Morgan Stanley Capital International World Index as a market proxy.

Panel B presents the One-way ANOVA F-statistic for the test of the null hypothesis that the systematic risk of all funds is equal. Column one is the period of observation. Columns two through five are the F-statistics for domestic only investors using the DJIA, S&P 500, CRSP EW, and CRSP VW as market proxies respectively. Column six is the F-statistic for globally diversified investors using the MSCI as a market proxy. The large F-statistic indicates the null hypothesis of equal risk can be rejected at the 0.01 confidence level for both types of investors over all three sample periods.

we do not pursue other benchmarks to examine risk-adjusted performance, we do examine the effects of other benchmarks on systematic risk.

4.2. Heterogeneity of investment objective risk classes

Once a target range of risk is selected, it must be mated to funds with appropriate characteristics. If the investment objectives result in mutually

Table 2
Average excess risk-adjusted returns by investment objective class

Classification	No. of funds	Average α from 9/81–9/94 by index				
		α_{DJ}	α_{SP}	α_{EW}	α_{VW}	α_{W}
Aggressive growth (*AG*)	43	-0.0043^{b}	-0.0035^{b}	-0.0045^{c}	-0.0046^{b}	0.0004
		(-2.05)	(-1.95)	(-2.89)	(-2.57)	(0.12)
Growth (*G*)	112	-0.0015	-0.0008	-0.0013	-0.0018^{b}	0.0023
		(-1.28)	(-1.16)	(-1.09)	(-2.59)	(0.93)
Growth and income (*GI*)	66	-0.0001	0.0004	0.0002	-0.0002	0.0028
		(-0.09)	(0.93)	(0.25)	(-0.61)	(1.53)
Balanced (*B*)	36	0.0007	0.0011^{a}	0.0011	0.0007	0.0031^{b}
		(0.84)	(1.91)	(1.25)	(1.38)	(2.01)
Bond and preferred stock (*BP*)	66	0.0029^{b}	0.0029^{b}	0.0034^{c}	0.0033^{c}	0.0036^{c}
		(2.43)	(2.57)	(2.88)	(2.83)	(3.25)
Municipal Bond (*MB*)	30	0.0020	0.0021	0.0027^{a}	0.0025^{a}	0.0031^{b}
		(1.43)	(1.51)	(1.87)	(1.74)	(2.18)
International (*IN*)	16	0.0009	0.0016	0.0011	0.0010	0.0027^{a}
		(0.44)	(0.80)	(0.54)	(0.46)	(1.90)
Metal (*ME*)	8	-0.0045	-0.0035	-0.0051	-0.0046	-0.0047
		(-0.62)	(-0.47)	(-0.67)	(-0.60)	(-0.65)

[a]Indicates significance at the 0.10 level.
[b]Indicates significance at the 0.05 level.
[c]Indicates significance at the 0.01 level.
Note: Column one provides the CDA investment objective, column two is the number of funds comprising the sample, and columns three through seven present the estimated risk adjusted excess returns for investors. α_{DJ} is estimated using the DJIA as a market proxy, α_{SP} is estimated using the S&P 500 as a market proxy, α_{EW} is estimated using the CRSP EW index as a market proxy, α_{VW} is estimated using the CRSP VW index as a market proxy, and α_{W} is the systematic risk for globally diversified investors estimated using the Morgan Stanley Capital International World Index as a market proxy. *t*-Statistics for the test of the null hypothesis that α equals zero are in parentheses.

exclusive risk classes, investors can compare funds within an investment objective group providing their desired level of risk. Following Reints and Vandenberg (1973) and Klemkosky (1976) we use the Sheffé test of contrasts to detect if the risk classes are statistically independent. A description of the Sheffé test can be found in Neter et al. (1990). Fifteen linear contrasts are examined to learn whether risk classes are mutually exclusive. These contrasts take the form:

$$\sum_{1}^{r} C_i U_i \varepsilon \sum_{1}^{r} C_i Y_i \pm [(r-1)F^{a}_{r-1,\,N-r}]^{1/2} s\left(\sum_{1}^{r} \frac{c_i^2}{n_i}\right)^{1/2} \tag{3}$$

Table 3
Results of Sheffé tests

Test No.	Class vs. Class	Significant difference at the 0.05 level for all indices?		
		9/81–3/88	3/88–9/94	9/81–9/94
1	*AG G*	Yes	Yes	Yes
2	*AG GI*	Yes	Yes	Yes
3	*AG B*	Yes	Yes	Yes
4	*AG BP*	Yes	Yes	Yes
5	*AG MB*	Yes	Yes	Yes
6	*G GI*	Yes	Yes	Yes
7	*G B*	Yes	Yes	Yes
8	*G BP*	Yes	Yes	Yes
9	*G MB*	Yes	Yes	Yes
10	*GI B*	Yes	Yes	Yes
11	*GI BP*	Yes	Yes	Yes
12	*GI MB*	Yes	Yes	Yes
13	*B BP*	Yes	Yes	Yes
14	*B MB*	Yes	Yes	Yes
15	*BP MB*	No	No	No

Note: Column one numbers the fifteen test-pair combinations. Columns two and three provide the pair of investment objectives compared. Columns four, five, and six provide the results for the hypothesis test that systematic risk is equal between the two groups during the three sampling periods. A yes answer means that the null hypothesis of equal risk was rejected. A no answer means that we fail to reject the null hypothesis of equal risk.

where C_i is linear contrasts, U_i is the population mean, $\bar{Y}_i$ is the estimated mean β of each cell, r is the number of columns, s is the square root of the mean square error, N is the total number of observations, n_i is the number of observations of each cell, and $F^{a}_{r-1,\,N-r}$ is the tabled F-value.

Results in Table 3 show that investment objectives provide a reasonable guide to the range of risk. Domestic fund classes are statistically different from one another with the exception of BP and MB funds.

4.3. Homogeneity within investment objective groups

The most important test is to find out whether the risk of each fund within a given investment objective subset is equal. This is vitally important in light of recent research on intertemporal risk changes and research on fund flows into "good funds". Do Klemkosky's (1976) results remain valid or has increased competition, compensation contracting, and imperfect monitoring provided an incentive for portfolio managers to alter risk?

Equation two is used to empirically estimate β's for each fund within the investment objective class. Table 4 shows that estimated β's for funds within

Table 4
The range and homogeneity of estimated betas by index and investment objective group

Investment objective	Number of funds	Index (maximum/minimum)				
		DJIA	S&P 500	CRSP EW	CRSP VW	W
AG	43	1.42/0.72	1.50/0.79	1.46/0.70	1.57/0.81	1.14/0.63
		2.41[b]	2.74[b]	3.14[b]	2.14[b]	0.51
G	112	1.17/0.40	1.24/0.45	1.18/0.36	1.29/0.47	0.94/0.38
		3.56[b]	4.61[b]	1.09	1.00	0.76
GI	66	1.01/0.23	1.04/0.24	0.93/0.25	1.06/0.25	0.80/0.19
		9.70[b]	13.13[b]	7.29[b]	9.96[b]	2.54[b]
B	36	0.92/0.29	0.95/0.31	0.88/0.30	0.99/0.32	0.73/0.25
		7.09[b]	7.91[b]	4.75[b]	1.00	1.47[a]
BP	66	0.65/0.00	0.66/0.00	0.67/0.00	0.68/0.00	0.52/0.00
		3.31[b]	2.47[b]	1.94[b]	2.59[b]	2.05[b]
MB	30	0.23/0.03	0.25/0.04	0.21/0.03	0.26/0.04	0.18/0.03
		3.19[b]	3.75[b]	2.22[b]	3.75[b]	1.67[a]
IN	16	1.24/0.55	1.28/0.54	1.27/0.54	1.34/0.56	1.04/0.53
		14.61[b]	9.77[b]	1.85[a]	0.72	10.37[b]
ME	8	0.60/0.34	0.51/0.23	0.56/0.30	0.52/0.26	0.82/0.68
		0.123	0.167	0.108	0.052	0.200

[a]Indicates significance at the 0.05 level.
[b]Indicates significance at the 0.01 level.
Note: Column one provides the CDA investment objective and column two is the number of funds comprising the sample. Columns three through seven are the range of systematic risk measures estimated using the DJIA, S&P 500, CRSP EW, CRSP VW and MSCI indices as market proxies respectively (mean β's are reported in Table 1). Below the range of beta estimates is the F-statistic for the One-way ANOVA F-test to determine if the risk differences observed are statistically significant or whether they can be attributed to chance. Results in column three indicate that seven of the eight investment objectives have heterogeneous within group risk at the 0.01 level from the perspective of domestic only investors holding portfolios with characteristics like those of the DJIA. Similar results are found with other indices.

each investment objective group vary widely, regardless of the market proxy (mean β's are reported in Table 1). Therefore, we test the hypothesis that risk is homogeneous within investment objective groups to learn if these differences are statistically significant.

To conduct statistical testing, β's are computed using monthly data over rolling one-year periods for the thirteen-year period September 1981–94. One-way ANOVA is then used to test the equality of β's within each investment objective group to learn if the average β for all funds within the investment objective group are equal. Formally, ANOVA will be utilized to test:

$$H_0:\quad \beta_{i,1,t} = \beta_{i,2,t} = \beta_{i,3,t} = \cdots = \beta_{i,n,t},$$

$$H_A:\quad \text{not all } \beta_i \text{ are equal.}$$

The null hypothesis is that the average systematic risk ($\beta_{i,n}$) for each fund within the investment objective group is equal. It is tested against the alternate hypothesis that at least one fund is not equal to the others. Our methodology follows Klemkosky (1976). The critical value of the F statistic (F^*) is computed using Eq. (4)

$$F^* = \frac{SSE(R) - SSE(F)}{df_R - df_F} \bigg/ \frac{SSE(F)}{df_F} \tag{4}$$

where $SSE(R)$ and $SSE(F)$ are the explained sum of squares for the reduced and full models respectively, and df_R and df_F are the degrees of freedom for the reduced and full models respectively.

Results in Table 4 suggest that the ability of investment objectives to convey risk may be overstated. Further, this result is independent of the proxy used for the investors portfolio holdings. Investors in funds may make ill-advised decisions if they attempt to select funds based on raw returns. Investors holding a portfolio similar to the DJIA or S&P 500 will be unable to use the investment objective classification to proxy systematic risk for any category of funds. The CRSP EW proxy does little better as only growth funds have undetectable risk differences on average. Holders of portfolios with characteristics similar to the CRSP VW index fair much better as they may be able to use the investment objective classification for selection of growth, balanced, and international funds.

Globally diversified investors are not as fortunate as those holding the CRSP VW index when it comes to using the investment objective classification to proxy for systematic risk. Only aggressive growth and growth funds seem to have homogeneous risk within the investment objective classification. Again, broad usage of investment objective classifications to proxy risk appears inappropriate.

One issue that arises is whether the way funds are classified fails to account for risk properly or whether risk parameters are simply being measured inaccurately. Since the estimated betas are index dependent, and previous studies (e.g., Brown and Brown, 1987; Lehmann and Modest, 1987) suggest that the practice of using stock indices to estimate bond fund betas is questionable, we also use bond fund indices to examine the robustness of our results. If our results for bond funds change dramatically when betas are measured against bond indices, the case of inaccurate risk measurement would be supported. Therefore, we use the Shearson Lehman Municipal Bond index to estimate betas for funds in the MB category and the Shearson Lehman Government & Corporate Bond index to estimate betas for the BP funds. We then repeated the previous analysis using these betas to test the robustness of our previous results.

Table 5 presents the results of One-way ANOVA tests of the null hypothesis that systematic risk is homogeneous within the MB and BP investment objective groups when betas are measured against bond indices. The F-statistic

Table 5
Homogeneity of bond fund systematic risk within CDA investment objective classes

Investment objective	F-statistic (p-value)
BP	0.0000
MB	0.0000

Note: This table presents further results of one-way ANOVA tests of the null hypothesis that systematic risk is homogeneous within investment objective groups. These results are achieved by using the Shearson Lehman Municipal Bond index to estimate betas for the municipal bond funds and the Shearson Lehman Corporate and Government Bond index to estimate the betas for the bond and preferred stock funds. Column one is the investment objective and column two presents the F-statistic p-value. The null hypothesis of risk homogeneity is rejected for both municipal bond and bond and preferred stock funds.

p-value suggests that the previous results are not driven by stock index induced measurement errors since the null hypothesis of risk homogeneity is rejected for both municipal bond and bond and preferred stock funds.

Another potential complication that arises is whether an investment objective does a good job of capturing dimensions of risk that are not measured by beta. While the risk tests presented previously for both measures of risk were equally descriptive, we test whether variance was equal in light of the evidence by Brown et al. (1996). These tests examine the total variability of fund returns within each investment objective group. Since the number of degrees of freedom for each of the n sample variances s_i^2 are equal, we use the Hartley test to determine whether differences in variance are significant. Formally, Hartley is used to test:

$$H_0: \quad \sigma_1^2 = \sigma_2^2 = \cdots = \sigma_r^2$$

$$H_A: \quad \text{not all } \sigma_i^2 \text{ are equal.}$$

Eq. (5) is used to compute the Hartley test statistic

$$H = \frac{\max(s_i^2)}{\min(s_i^2)} \tag{5}$$

where H is the Hartley statistic, max s_i^2 is the maximum sample variance and min s_i^2 is the minimum sample variance.[12] Critical H values are from David (1952).

The Hartley test results, reported in Table 6, support the systematic risk test results reported previously. In all eight investment objective classes the hypothesis of equal within group variance is rejected at the 0.01 level.

[12] Since outliers could affect the results of the Hartley test, we examined our data to ensure that outliers did not drive our results.

Table 6
Homogeneity of total risk within CDA investment objective classes

Investment objective	Number of funds	Minimum variance	Maximum variance	Hartley statistic
AG	43	0.0017	0.0060	3.4509[b]
G	112	0.0009	0.0038	4.2409[a]
GI	66	0.0003	0.0024	8.4641[b]
B	36	0.0004	0.0022	5.2132[b]
BP	66	0.0000	0.0013	250.2791[b]
MB	30	0.0000	0.0007	56.6483[b]
IN	16	0.0009	0.0040	4.5828[b]
ME	8	0.0053	0.0177	3.3173[b]

[a]Indicates significance at the 0.05 level.
[b]Indicates significance at the 0.01 level.
Note: This table presents the results of the Hartley test on the total variance of funds within each of the eight CDA investment objective classes for the total sample during the September 1981–September 1994 period. Columns one and two provide the investment objective classification and the number of funds included in the sample, respectively. Column three provides the variance of the fund in the sample with the lowest variance over the 156-month sample period. Column four provides the variance of the fund in the sample with the highest variance over the 156-month sample period. Column five provides the Hartley statistic which is used to test whether the sample variances are significantly different.

4.4. The classification of funds and robustness of within group risk heterogeneity results

One plausible explanation for the apparent failure of investment objective to appropriately convey risk is that the classification scheme fails to account for some important characteristics that affect risk. Greer (1997) defines an asset class as a 'set of assets that bear some fundamental economic similarities to each other, and that have characteristics that make them distinct from other assets that are not part of the class'. While the classification of some funds may seem to be obvious, others are not. For example, it may be quite easy to classify municipal bond or precious metal funds given their stated investment objectives to invest in restricted categories of assets. However, what is the difference between two adjacent equity fund classifications? What are the criteria used to discern whether a fund is classified as a growth fund, or whether is really an aggressive growth fund? Is there really a difference between the risk of growth funds and growth and income funds or is this simply a way to create clienteles across people who prefer current income versus capital appreciation? These questions are not as easy to answer. While the previous literature has assumed that investment objectives and risk are related in some tractable way, our results suggest that this may no longer be the case. This could be due to either a failure of classification schemes to capture all the important elements of risk or the ability of portfolio managers to game risk.

To learn how funds are classified into various investment objective classes, we contacted CDA Investment Technologies, Inc., and Lipper Analytical Services. Classifying funds is a knotty issue and each classification scheme appears to produce categories that some may consider similar, but not identical classifications. While each firm uses its own proprietary methodology to classify funds, the determination of the appropriate risk classification depended upon factors detailed in the prospectus or quantitatively derived. These factors can include the stated objectives of the fund, normal (current) asset allocation, ability to use derivatives, short selling, borrowing and lending securities, duration and default risk of bonds, average market capitalization and whether the securities selected are considered value or growth stocks. Quantitative techniques, such as those proposed by Sharpe and Cooper (1972), may also be used. Sharpe and Cooper (1972) examine the risk-return classes of NYSE common stocks by examining their market sensitivity over a five-year period. They then sort stocks into ten portfolios based on ex ante risk After comparing the ex ante risk with risk measured in subsequent periods, they conclude that risk of both portfolios and individual securities is relatively stable over time. Thus, the asset allocation among ex ante risk deciles may provide a clue to the classification.

One important issue is whether the failure of investment objectives to convey risk is unique to CDA classifications. An issue closely related to classification is the issue of 'style'. Tierney and Winston (1991) use size and P/E ratios to characterize style whereas Sharpe (1992) uses factor loadings. Both studies claim to produce styles not captured by standard classification systems. However, neither of these studies classifies funds in a way that would enable us to examine the within group risk homogeneity of their classification scheme. Moreover, neither study tests for risk homogeneity within their investment objective classifications. Brown and Goetzmann (1997) also study style and conclude that standard investment objective classifications allow for a wide range of styles (investment polices). But they also neglect to test the homogeneity of within class systematic risk.

To examine whether our results are driven by the CDA categories, we present the results for two other classification schemes. First, we use the Lipper categories (as presented in the Wall Street Journal at the end of our classification period). Second, we use the classification system of Brown and Goetzmann (1997).

We consulted the *Wall Street Journal* to determine the appropriate investment objective of each fund. Of the original 377 fund sample, only 352 funds are classified in the *Wall Street Journal* and represent twenty-two unique investment objective classes. The composition of the sample is 7 *MID*, 7 *SML*, 8 *WOR*, 76 *GRO*, 26 *CAP*, 19 *SEC*, 12 *EQI*, 69 *GI*, 28 *SB*, 19 *GLM*, 8 *ITL*, 20 *BHI*, 28 *BND*, 7 *MTG*. Due to the small number of funds comprising some investment objective

Table 7
Homogeneity of risk within wall street journal investment objective classes

Investment objective	Number of funds	Index (p-value)				
		DJIA	S&P 500	CRSP EW	CRSP VW	W
MID	7	0.0000	0.0000	0.0000	0.0000	0.0843
SML	7	0.0014	0.0005	0.0000	0.0006	0.5544
WOR	8	0.0000	0.0000	0.0000	0.0262	0.0000
GRO	76	0.0000	0.0000	0.4578	0.0000	0.1636
CAP	26	0.0000	0.0000	0.0000	0.0000	0.7979
SEC	19	0.0000	0.0000	0.0002	0.4575	0.0199
EQI	12	0.0000	0.0000	0.0000	0.0000	0.0004
GI	69	0.0000	0.0000	0.0000	0.4812	0.0151
SB	28	0.0000	0.0000	0.0000	0.4701	0.0774
GLM	19	0.0000	0.0000	0.0000	0.0000	0.0000
ITL	8	0.0000	0.0001	0.8082	0.9715	0.0005
BHI	20	0.9976	0.9997	0.7024	0.9988	0.9999
BND	28	0.0000	0.0000	0.0000	0.0000	0.0000
MTG	7	0.8751	0.9476	0.9893	0.9048	0.8477

Note: This table presents results of the one-way ANOVA F-test to determine if the risk differences observed remain after controlling for classification schemes. Column one provides the investment objective and column two is the number of funds comprising the sample. Columns three through six are the ANOVA F-statistic p-values for the null hypothesis that the risk for domestic only investors is homogeneous within the investment objective group. They are provided for the DJIA, S&P 500, CRSP EW, and VW indices respectively. Column seven is the ANOVA p-value for the null hypothesis test that the risk for globally diversified investors (MSCI) is homogeneous within the investment objective group. Results in column three indicate that twelve of the fourteen investment objectives have heterogeneous within-group risk at the 0.01 level from the perspective of domestic only investors holding portfolios with characteristics like those of the DJIA. Similar results are found with other indices.

classes, eight classes were not evaluated. Thus, the evaluation focuses on fourteen investment objective classes and the 334 funds that comprise them.

The procedure we use to analyze within group risk heterogeneity of Lipper classifications is identical to the procedure we used previously to examine the CDA classification scheme. In Table 7, column three indicates that twelve of the fourteen investment objectives have heterogeneous within-group risk at the 0.01 level from the perspective of domestic only investors holding portfolios with characteristics like those of the DJIA. Similar results are found with other indices.

Brown and Goetzmann (1997) propose an alternate classification scheme to capture style. Since it is plausible that popular classification schemes fail to capture important components of variability that is style related, we also test the Brown and Goetzmann stylistic classification to ascertain its robustness. The

Table 8
Homogeneity of risk within Brown and Goetzmann investment objective classes

Investment objective	Number of funds	Index (p-value)				
		DJIA	S&P 500	CRSP EW	CRSP VW	W
G	61	0.0000	0.0000	0.0000	0.0000	0.9996
GLAM	12	0.2547	0.1550	0.0355	0.0498	0.9483
VAL	22	0.0000	0.0000	0.0000	0.2263	0.2321
GI	71	0.0002	0.0000	0.0001	0.0000	0.9993
I	41	0.0000	0.0000	0.0000	0.0000	0.0000
GT	5	0.0091	0.1420	0.4606	0.7452	0.0001
IN	4	0.1857	0.8417	0.9151	0.9702	0.0004
ME	6	0.9990	0.9998	0.9999	0.9999	0.9736

Note: This table presents results of the one-way ANOVA F-test to determine if the risk differences observed remain after controlling for classification schemes. Column one provides the investment objective and column two is the number of funds comprising the sample. Columns three through six are the ANOVA F-statistic p-values for the null hypothesis that the risk for domestic only investors is homogeneous within the investment objective group. They are provided for the DJIA, S&P 500, CRSP EW, and VW indices respectively. Column seven is the ANOVA p-value for the null hypothesis test that the risk for globally diversified investors (MSCI) is homogeneous within the investment objective group. Results in column three indicate that five of the eight investment objectives have heterogeneous within-group risk at the 0.01 level from the perspective of domestic only investors holding portfolios with characteristics like those of the DJIA.

Brown and Goetzmann stylistic classification system consists of eight classes; growth (*G*), glamour (*GLAM*), value (*VAL*), growth and income (*G*), income (*I*), global timing (*GT*), international (*IN*), and metal (*ME*). To determine whether this classification scheme has the ability to correct the risk heterogeneity discovered in the other two classifications we tested, we reclassified funds in our sample using the classifications posted on Will Goetzmann's home page. This results in a usable sample of 61 (*G*), 12 (*GLAM*), 22 (*VAL*), 71 (*GI*), 41 (*I*), 5 (*GT*), 4 (*IN*) and 6 (*ME*).

Column three in Table 8 indicates that five of the eight investment objectives have heterogeneous within group risk at the 0.01 level from the perspective of domestic only investors holding portfolios with characteristics like those of the DJIA. Therefore, it appears that this stylistic classification also misses some important characteristic of risk or that the portfolio managers manipulate risk in important ways.

5. Conclusion

This paper examines whether the stated investment objectives of mutual funds adequately represent risk to investors. This is extremely important if an investor attempts to compare returns to select an investment within an investment objective class. For investors to be able to make utility maximizing decisions based on returns, investment objective classes must be systematically and consistently related to the level of systematic risk faced by the investor. If systematic risk is not homogeneous within investment objective classes, comparison of returns is highly suspect and may lead to selecting the most risky fund.

Our empirical findings reveal that while risk is heterogeneous between investment objective classes, there are substantial differences within a given class. Further, this finding is robust with respect to the selected classification scheme and the market portfolio used in the estimation of systematic risk. Examination of total risk provides confirmatory evidence that standard investment objective classifications fail to completely capture risk. This within-group risk heterogeneity may be exacerbated by the intense competition in the mutual fund industry, imperfect monitoring by the SEC and investors, and portfolio manager compensation contracting. Another explanation is that the classification system fails to properly consider some important element into the classification.

Appendix A. Description of mutual fund investment objective classifications

Aggressive growth – Typically invest in stocks of up-and-coming new firms considered to possess tremendous potential. However, firms have little current cash flow. These funds seek rapid growth of capital and use investment techniques involving greater-than-average risk (e.g., short-selling, frequent trading, and leveraging).

Growth – Slightly less risky than aggressive growth funds. Typically invest in established, fast growing large or mid-sized companies thought to have solid prospects for continued future growth.

Growth and income – Considered middle-of-the-road equity funds and favor stocks of well-established large companies that pay dividends.

Balanced – Hybrids that invest primarily in the stocks and bonds of large companies in a proportion of about 60% stock and 40% bonds.

Bond and preferred stock – Invest in senior securities, bonds and preferred stock, with the goal of current income and preservation of capital.

Municipal bond – Invest in municipal bonds with the objective of providing stable after tax income.

International – Invest in the securities of foreign firms.

Metal – Seek capital appreciation by investing in the stocks of firms engaged in the mining, distribution, or processing of precious metals.

References

Bogle, J.C., 1970. Mutual fund performance evaluation. Financial Analysts Journal 26, 25–33.
Bogle, J.C., 1991. Investing in the 1990s: Remembrance of things past and things yet to come. Journal of Portfolio Management 17, 5–14.
Bowen, J.J., Statman, M., 1997. Performance games. Journal of Portfolio Management 23, 8–15.
Brown, K.C., Brown, G.D., 1987. Does the composition of the market portfolio really matter? Journal of Portfolio Management (Winter), 26–32.
Brown, K.C., Harlow, W.V., Starks, L.T., 1996. Of tournaments and temptations: an analysis of managerial incentives in the mutual fund industry. Journal of Finance 51, 85–110.
Brown, S., Goetzmann, W., 1997. Mutual fund styles. Journal of Financial Economics 43, 373–399.
Brown, S., Goetzmann, W., Ibbotson, R., Ross, S., 1992. Survivorship bias in performance studies. Review of Financial Studies 5, 553–580.
Capon, N., Fitzsimons, G.J., Prince, R.A., 1996. An individual level analysis of the mutual fund investment decision. Journal of Financial Services Research 10, 59–82.
Carlson, R.S., 1970. Aggregate performance of mutual funds 1948–1967. Journal of Financial and Quantitative Analysis 5, 1–32.
Chevalier, J., Ellison, G., 1995. Risk taking by mutual funds as a response to incentives. NBER Working Paper Number 5234.
Christopherson, J.A., 1995. Equity style classifications. Journal of Portfolio Management 21, 32–43.
Cohen, S., Starks, L., 1988. Estimation risk and incentive contracts for portfolio managers. Management Science 34, 1067–1080.
David, H.A., 1952. Upper 5 and 1% points of the maximum F-ratio. Biometrika 39, 422–424.
Goetzmann, W., Greenwald, B., Huberman, G., 1992. Market response to mutual fund performance, Working paper. Columbia University.
Goetzmann, W.N., Peles, N., 1997. Cognitive dissonance and mutual fund investors. Journal of Financial Research 20, 145–158.
Golec, J., 1992. Empirical tests of a principal-agent model of the investor–investment advisor relationship. Journal of Financial and Quantitative Analysis 27, 81–96.
Greer, R.J., 1997. What is an asset class, anyway? Journal of Portfolio Management 23, 86–91.
Grinblatt, M., Titman, S., 1987. How clients can win the gaming game. Journal of Portfolio Management 13, 14–20.
Grinblatt, M., Titman, S., 1989a. Mutual fund performance: an analysis of quarterly portfolio holdings. Journal of Business 62, 393–416.
Grinblatt, M., Titman, S., 1989b. Portfolio performance evaluation: old issues and new insights. Review of Financial Studies 2, 393–421.
Grinblatt, M., Titman, S., 1993. Performance measurement without benchmarks: an examination of mutual fund returns. Journal of Business 66, 47–68.
Grinold, R., Rudd, A., 1987. Incentive fees: who wins? Who loses? Financial Analysts Journal 43, 27–38.
Ippolito, R.A., 1989. Efficiency with costly information: a study of mutual fund performance. 1965–1984. Quarterly Journal of Economics 104, 1–23.
Ippolito, R.A., 1992. Consumer reaction to measures of poor quality: evidence from the mutual fund industry. Journal of law and Economics 35, 45–70.
Jensen, M., 1968. The performance of mutual funds in the period 1945–1964. Journal of Finance 23, 389–419.

Klemkosky, R.C., 1976. Additional evidence on the risk level discriminatory powers of the Weisenberger classifications. Journal of Business 45, 48–50.

Kritzman, M., 1987. Incentive fees: some problems and some solutions. Financial Analysts Journal 43, 21–26.

Lehmann, B.N., Modest, D.M., 1987. Mutual fund performance evaluation: a comparison of benchmarks and benchmark comparisons. Journal of Finance 42, 233–265.

Malkiel, B.G., 1995. Returns from investing in equity mutual funds 1971–1991. Journal of Finance 50, 549–572.

McDonald, J.G., 1974. Objectives and performance of mutual funds. Journal of Financial and Quantitative Analysis 9, 311–333.

Neter, J., Wasserman, W., Kutner, M., 1990. Applied Linear Statistical Models third ed. Irwin, Homewood.

Orphanides, A., 1996. Compensation incentives and risk taking behavior: evidence from mutual funds. Finance and Economics Discussion Series # 96-21, Federal Reserve Board, Washington, D.C.

Reints, W.W., Vandenberg, P.A., 1973. A comment on the risk level discriminatory powers of the Weisenberger classifications. Journal of Business 46, 278–283.

Roll, R., 1978. Ambiguity when performance is measured by the security market line. Journal of Finance 33, 1051–1069.

Sharpe, W.F., 1966. Mutual fund performance. Journal of Business 39, 119–138.

Sharpe, W.F., 1992. Asset allocation: Management style and performance measurement. Journal of Portfolio Management 18, 7–19.

Sharpe, W.F., Cooper, G.M., 1972. Risk-return classes of New York stock exchange common stocks, 1931–1967. Financial Analysts Journal 28, 46–54.

Sirri, E., Tufano, P., 1992. The demand for mutual fund services by individual investors. Harvard Business School Working Paper.

Starks, L.T., 1987. Performance incentive fees: An agency theoretic approach. Journal of Financial and Quantitative Analysis 22, 17–32.

Tierney, D.E., Winston, K., 1991. Using generic benchmarks to present manager styles. Journal of Portfolio Management 17, 33–36.