What individual investors should know about load effects on mutual fund risk

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Abstract

I examine the validity of the practice of using hypothetical investment returns from a sample of mutual funds in a selected investment objective classification and comparing total returns to make fund selection. While early research supported this practice by showing that risk is homogeneous within investment objective groups, more recent research suggests that risk is heterogeneous within investment objective groups. Research also suggests that load and no-load funds may exhibit risk differences. I extend the research in this area to examine whether risk is homogeneous within investment classification and heterogeneous between classes. Results reveal that practitioners and investors should be leery of selecting funds based solely on hypothetical investment returns because significant risk differences exist even after controlling for the load structure of the fund.

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1. Introduction

The central tenant in finance that risk and return are essential elements in selecting investments is illustrated in the theory of utility maximization and embedded in performance measures such as the Shape, Treynor, Jensen, and M^2. Utility theory suggests that understanding the risk and return of mutual funds is crucial to practitioners and investors in order to maximize the investors' satisfaction (utility) with the investment that they have chosen. From an investor's perspective, this is important because every investor wants to feel comfortable with their investment choices. From a practitioner's perspective, satisfying investors may result in increased business through better retention of existing clients and word-of-mouth referrals from satisfied clients.

Many mutual funds exist from which investors can choose in building their investment portfolio. Practitioners often assist with the selection process by ascertaining the investors risk tolerance and then providing hypothetical investment results of suitable mutual funds that illustrate the return of various investment options. Investors then use the hypothetical investment results to compare the returns that would have been achieved if an investment had been made in the selected funds. This approach provides the investors with a benchmark that they can use to assess the relative performance of their investments.

The above approach is suitable if the investment objectives properly convey risk as suggested by Sharpe (1966) and Klemkosky (1976). However, for investment objectives to properly convey risk, the objectives must be systematically related to a quantitative measure of risk such as beta or volatility. Also, risk must be homogeneous within investment objective and heterogeneous between classes. However, if the risks of funds within an investment objective class differ, comparing returns alone is insufficient to make utility maximizing investment decisions. Unfortunately, Najand

and Prather (1999) reported that risk is heterogeneous within investment objective groups. Therefore, the practice of comparing returns does not appear optimal.

I extend the work of Najand and Prather (1999) to incorporate the findings of Chordia (1996) that no-load fund portfolio managers hold more cash to meet a higher level of uncertain redemptions. This implies that systemic differences in risk between load and no-load funds may occur. Malhotra and McLeod (1997) also reported that load and no-load funds may have risk differences because they found that no-load funds have a higher cash ratio. Chordia's (1996) work suggests that one factor that may drive the reported risk heterogeneity is that risks differ systematically between load and no-load funds. Chordia (1996) characterized no-load fund investors as less loyal to a fund that performs poorly. Therefore, no-load fund managers must be sensitive to performance. This is consistent with the findings of Brown, Harlow and Starks (1996) that the "tournament" effect that is strongest with no-load funds. If more frequent switching by no-load fund investors causes no-load fund portfolio managers to respond by holding more cash to meet uncertain redemptions, that singular action could cause no-load funds to have lower risk than load funds in the same investment objective if investment constraints results in similar portfolios of risky assets.

2. Data sources and methodology

Thirteen years of monthly return data was obtained from CDA Investment Technology, Incorporated and screened using a process similar to that of Grinblatt and Titman (1989, 1992, 1993, 1994) and Najand and Prather (1999). Table 1 presents the sample size by the CDA investment objective classification. Since several different classification schemes exist, I examine the robustness of results by using CDA, *Wall Street Journal* (Lipper Analytical Services) and Brown and Goetzmann (1997) classification schemes.

<Insert Table 1 about here>

CDA's return data is also used for the S&P 500 Index, Dow Jones Industrial Average (DJIA), and the risk-free proxy (90-day T-bill return) while The Center for Research in Security Prices (CRSP) return data is used 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 as a benchmark for globally diversified investors. Because Brown and Brown (1987) and Lehmann and Modest (1987) reported that the selection of the index can have substantial impact on performance evaluation, using multiple indices when computing risk measures helps ensure that the results are robust with respect to the index. These particular indices may be important benchmarks for investors because they may provide a good proxy for the investor's current portfolio. For example, investors that hold primarily "blue chip" stocks may find that the DJIA is the closest proxy to their portfolio while investors that are primarily S&P 500 index may find that the S&P 500 is the best proxy. However, globally diversified investors may find that the MSCI is the best proxy.

2.1. Potential sources of bias

The sample selection process may result in two unavoidable types of bias: "survivorship" bias and "omission" bias. Omission bias may exist whenever newer funds are excluded from analysis. Arteaga, Ciccotello, and Grant (1998) reported that return bias can be created through mutual fund incubation. They argued that seed money could be used to create multiple funds, each taking multiple successive bets in an uncertain world. After the outcomes are known, winning funds would be marketed and losing funds dropped. Since it is unlikely that incubation bias is something new, if incubation exists, excluding funds that commenced operation after the sample period began may strengthen the validity of my results. This is because admitting these "new" and alleged riskier funds into the sample could cloud my results since the subsample with the highest proportion of "new" funds may have skewed return distributions (more nonsystematic risk and less systematic risk) or higher systematic risk. Brown, Harlow, and Starks (1996) provide additional motivation for excluding "new" funds since they find that newer funds exhibit more of a "tournament" effect than seasoned funds. Since my interest is differential risk between load and no-load funds, excluding "new" funds removes the possible extraneous noise created by those funds. If omission bias does not exist, then new funds could be expected to exhibit risk-return relationships similar to existing funds. Under that scenario, excluding new funds should not materially influence the results.

Brown, Goetzmann, Ibbotson, and Ross (1992) show that survivorship bias exists when extinct mutual funds are excluded from analysis. This is particularly troubling when examining whether managers could outperform an unmanaged index since in efficient markets, poorly performing funds should become extinct. This leaves the better performing funds to compare against the index. Therefore, survivorship bias would cause the measured performance of the sample of funds to be overstated relative to the index.

However, important theoretical differences exist between this study and studies that examine the relative performance of managed funds and an unmanaged index. These differences may cause survivorship bias to affect this study differently than it affected performance studies. The critical difference between the two types of studies is that when a study is undertaken that compares the performance of managed portfolios to an index, and poorly performing portfolios become extinct, only better performing portfolios remain to be examined. This poor performance could be explained by economic theory if it resulted from poor security selection, poor market timing, or inefficient operations that led to high expenses. Therefore, portfolio extinction is understandable in terms of economic theory and the effect of this bias is obvious.

In a study of whether one group of managed portfolios exhibits different risk characteristics than another group of managed portfolios due to the type of fee structure, the effect of survivorship bias is less clear. This requires critically examining the theoretical reasons for extinction and the consequent impact of that extinction on the sample to be studied. If we assume that extinction is related to either poor portfolio management or poor operations, the degree of bias would hinge critically on the relative extinction of both sets of managed portfolios. First, assume that extinction is a result of inefficient operations. I can think of no *a priori* reason to believe that there is an inherent difference in operational inefficiency between load and no-load funds. Therefore, to the extent that extinction is related to inefficiency, this facet of extinction could be expected to be random. Thus, it would also be expected to have an equal effect on both load and no-load funds. If this is the case, survivorship bias should not be expected to have a material influence on our results. Second, extinction may be related to the quality of portfolio management. If performance outcomes can be assumed to be the result of the quality of portfolio management decisions, on average, then extinction should be related to the quality of decision making. However, based on the findings of Agarwal and Prather (1997), Droms and Walker (1994), and Gruber (1996), there does not appear to be any *a priori* reason to believe that differential management quality exists between load and no-load funds exist since the risk-adjusted returns do not differ significantly.

By examining the risk characteristics of only surviving funds, I eliminate any confounding effects caused by portfolio managers who took on undue risk that backfired, causing the funds to perform poorly and become extinct. However, only surviving funds can be examined empirically and the effect of survivorship bias cannot be determined.

2.2. Computation of returns

Continuously compounded monthly net returns are computed by taking the natural log of the change in wealth over each of the 156-month holding periods as shown in equation one.

$$R_{i,t} = \ln\left[\frac{NAV_{i,t} + DV_i + CG_i}{NAV_{i,t-1}}\right] \qquad (1)$$

where: $R_{i,t}$ is the return on fund i during period t, NAV_{it} is the net asset value of fund i at time t, DV_i is the dividend and interest paid on fund i during the period, and CG_i is the capital gain distribution paid on fund i during the period. Index returns are computed similarly.

2.3. Determination of systematic risk

Systematic risk is determined by using ordinary least squares regression (OLS) and the Capital Asset Pricing Model (CAPM). The model used is:

$$R_{mf,t} - R_{f,t} = \alpha + \beta(R_{M,t} - R_{f,t}) + \varepsilon_t \qquad (2)$$

where R_{mf} is the return on the mutual fund, R_f is the return on the risk-free asset (90-day T-bill), and R_m is the return on the market proxy. 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. If the investment objective classification conveys risk, the β's for funds within each investment objective classification should not differ significantly from one another for a given index, although it may differ for different indices.

3. Empirical results

The mutual fund's prospectus details specific constraints about the investment composition of the fund and cannot be changed without shareholder approval since it would alter the basic characteristics of the investment. Based, at least in part, on this information, funds are classified into an investment objective. If investment constraints are binding and the investment objectives are good surrogates for risk, risk should be homogeneous within an investment objective group and heterogeneous between groups. To examine the usefulness of investment objectives as risk proxies, the risks that investors would experience had they invested in the funds are estimated.

Table 2 presents the results of estimating β's for each fund over the 156-month period. Betas can vary with the selected index since $\beta = (\text{Cov } Ri,Rm)/\sigma_m^2$ therefore, five indices were utilized to ascertain the impact of index selection on beta computation. The results suggest that the systematic risk of funds within each investment objective group vary widely, despite the selected market proxy. Table 2 column one provides the CDA investment objective and column two provides the number of funds comprising the sample. Columns three through seven are the systematic risk measures estimated using the DJIA, S&P 500, CRSP EW, CRSP VW, and MSCI (W) indexes as market proxies. The large range in estimated systematic risk is consistent with the findings of Najand and Prather (1999) and suggests that risk may not be homogeneous within each investment objective classification. Therefore, I now test the hypothesis that risk is homogeneous within investment objective groups to find out if these differences are statistically significant or due solely to chance.

<Insert Table 2 about here >

3.1. Systematic risk homogeneity tests

To conduct statistical testing, βs are computed using monthly data over rolling one-year periods for the thirteen-year period. This provides a distribution of 144 βs for each of the 323 funds for each of the five indexes. These βs are then compared using One-way ANOVA to test the equality of βs 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:

$$HO: \beta_{i,1,t} = \beta_{i,2,t} = \beta_{i,3,t} = \ldots = \beta_{i,n,t}$$

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

The null hypothesis is that the average systematic risk ($\beta_{i,n}$) for each fund within the investment objective group is equal. My methodology follows Klemkosky (1976) and Najand and Prather (1999). The critical value of the F statistic (F^*) is computed using equation three

$$F^* = \frac{SSE(R) - SSE(F)}{df_R - df_F} \div \frac{SSE(F)}{df_F} \tag{3}$$

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.

Table 3 presents results of the one-way ANOVA F-test to determine if the risk differences reported in Table 2 are statistically significant or whether they can be attributed to chance. Column one provides the CDA investment objective and column two is the number of funds comprising the sample. Columns three through seven are the ANOVA F-statistics for testing the null hypotheses that the risks for investors are homogeneous within the investment objective groups. Results in column three indicate that all of the investment objectives have heterogeneous within group risk at the .01 level from the perspective of investors holding portfolios with characteristics like those of the DJIA. Similar results are found with other indices.

<Insert Table 3 about here >

3.2. Differences in systematic risk between load and no-load funds

Chordia (1996) and Malhotra and McLeod (1997) reported that load funds hold less cash than no-load funds. Presumably, this is due to a more stable clientele and redemptions that are more predictable. The act of holding dissimilar amounts of cash could cause systemic differences in risk between load and no-load funds. If no-load funds hold more cash and fewer risky assets, they would be less risky *ceteris paribus* because the standard deviation of a portfolio (σ_p) is equal to the product of the weight in the risky asset (w_r) and the standard deviation of the risky asset (σ_r) or $\sigma_p = w_r (\sigma_r)$. Therefore, as the proportion of cash increases (w_c), the proportion of the total investment in the risky portfolio (w_r) decreases and so does the standard deviation of the portfolio (σ_p). This would decrease the systematic risk (β) as well since $\beta_p = \rho(\sigma_p / \sigma_m)$, where ρ is the correlation between the portfolio and the market and σ_p and σ_m are the portfolio and market variabilities, respectively. Alternatively, the beta of a portfolio is the weighted sum of the beta of each asset times the beta of the asset. Because the beta of cash is zero, a portfolio with higher cash holdings would have a smaller beta *ceteris paribus*.

Brown, Harlow, and Starks (1996) found that no-load fund managers with a poor performance record in the first half of the year alter risk in the second half of the year to improve performance suggesting that no-load funds investors may be more sensitive to performance. Chordia (1996) believes that is the case and that switching costs create differences in loyalty between load and no-load fund investors. He believes that this mitigates fund flows for load funds and therefore creates different effects for load and no-load portfolio managers. Therefore, the load structure may explain the documented heterogeneous within group risk.

To test the hypothesis that systematic risk is homogeneous between the load and no-load funds for each investment objective, the sample was segmented into two groups, load funds and no-load funds. This division provides a sample of 180 load funds consisting of 21 (AG), 52 (G), 39 (GI), 22 (B), and 46 (BP). The remainder of the sample consists of 143 no-load funds broken down into 22 (AG), 60 (G), 27 (GI), 14 (B), and 20 (BP). The monthly returns from each group are computed to provide an equally weighted 156-month index return from each group. Using equally weighted indexes is important since the objective is to determine the similarity of risk between the average load fund and the average no-load fund in a selected investment objective. Once the indices were computed, a modified market model, equation four, was used to determine the relative systematic risk.

$$R_{LDI,t} - R_{f,t} = \alpha + \beta (R_{NLI,t} - R_{f,t}) + \varepsilon_t \qquad (4)$$

where $R_{LD,t}$ is the return on the load fund index for a given investment objective group during each month t of the 156-month sample period, $R_{f,t}$ is the risk-free rate of interest (90 day U.S. T-bills), $R_{NL,t}$ is the return on the no-load fund index for a given investment objective group during each month t of the 156-month sample period, and α and β are the estimated excess risk-adjusted return and systematic risk coefficients. This permits determining whether the average risk of load funds differs systematically from that of no-load funds. If the risk of load and no-load funds is the same, the estimated β coefficient should not differ statistically from one.

Table 4 shows that the risk of load funds is statistically greater than that of no-load funds. Column one is the CDA investment objective group. Columns two through four provide the sample size for the total sample, the load fund sample, and the no-load fund sample respectively. Column five provides the systematic risk estimate generated by regressing the returns of the index of load funds on the index of no-load funds and column six is the adjusted coefficient of determination of the model. A beta of one would suggest equal risk whereas a beta with a confidence interval that excludes one would suggest that risk is significantly different between the two groups. Results suggest that systemic differences exist and the differences in risk are significant at the .05 level. These results are consistent with no-load portfolio managers holding more cash (e.g., Chordia (1996), Malhotra and McLeod (1997)) and having similar risky asset portfolio compositions. At a minimum, these findings suggest that comparing funds within investment objective classes without considering the fee structure can be misleading.

<Insert Table 4 about here >

3.3. Load adjusted systematic risk homogeneity tests

To determine if systemic differences in risk between load and no-load funds were the sole cause of heterogeneous within group risk, the sample was partitioned into load and no-load sub samples and one-way ANOVA on betas was repeated for each sub sample. To conduct statistical testing, βs are computed using monthly data over rolling one-year periods for the thirteen-year period. This provides a distribution of βs for each fund. These βs are then compared using One-way ANOVA to test the equality of βs within each investment objective group for each load structure to learn if the average β for all funds within the investment objective group are then equal.

Table 5 presents results of the one-way ANOVA F-test to determine if risk differences reported in Table 3 remain after controlling for load effects. Column one provides the CDA investment objective and column two is the number of funds comprising the sample. Columns three through seven are the ANOVA F-statistic p-values for the null hypothesis that the risk for investors is homogeneous within the investment objective group. Results in panel A, column three, indicate that all five investment objectives have heterogeneous within group risk at the .01 level from the perspective of investors holding portfolios with characteristics like those of the DJIA. Similar results are found with other indices. Therefore, load fund investors should be wary of simply using CDA investment objective classifications to compare the risk of funds.

Similar results are obtained when the no-load sub sample is examined, as reported in panel B. Results in column three indicate that all five investment objectives have heterogeneous within group risk at the .01 level from the perspective of investors holding portfolios with characteristics like those of the DJIA. Similar results are found with other indices. Therefore, no-load fund investors should also be wary of simply using CDA investment objective classifications to compare the risk of funds. These results suggest that differences in cash holding by load and no-load funds managers are not the sole driver of risk heterogeneity although they do appear to create important differences in risk between load and no-load funds.

<Insert Table 5 about here >

3.4. Examination of total risk

Najand and Prather (1999) question whether investment objectives may do a good job of capturing elements of risk that are not captured by beta. Therefore, they examine the total variability of fund returns within each investment objective group. Since the number of degrees of freedom for each of the r sample variances s_i^2 is equal, they use the Hartley test to determine whether differences in variance are significant. I also use the Hartley test to examine total risk over the 156-month period. Formally, Hartley is used to test:

$$HO: \sigma_1^2 = \sigma_2^2 = \ldots = \sigma_r^2$$

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

Equation 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. Critical H values are from David (1952).

Table 6 presents the results of the Hartley test on the total variance of funds within each of the CDA investment objective classes. 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 funds in the sample with the lowest variance and column four provides the variance of the funds in the sample with the highest variance. Column five provides the Hartley statistic, which is used to test whether the sample variances are significantly different. Results are presented for the load fund sample and the no-load fund sample in panels A and B, respectively. Hartley statistics suggests that the total risk is heterogeneous within each of the CDA investment objective groups after controlling for risk differences between load and no-load funds.

<Insert Table 6 about here >

3.5. Effect of classification schemes on systematic risk differences

To investigate the robustness of the results with respect to the classification scheme, the sample was reclassified into the investment objectives listed in the *Wall Street Journal* (Lipper Analytical Services) and those of Brown and Goetzmann (1997). Table 7 presents the results of repeating the tests on load and no-load funds reported in Table 4 after reclassifying the sample. Panel A presents results for Brown and Goetzmann's classification scheme while panel B presents results for the *Wall Street Journal's* classification scheme. Panel A shows that significant differences between load and no-load funds exist for each investment objective classification. However, load funds do not continue to be systematically riskier as Chordia (1996) suggests. Panel B shows that two of the four investment classifications exhibit significantly different risk between load and no-load funds. However, the direction of risk differences between load and no-load funds for the two groups is opposite. The analysis suggests that while Chordia's (1996) explanation of the direction of risk differences between load and no-load funds is not robust to the classification scheme, correcting for fee structure may improve within class risk homogeneity.

<Insert Table 7 about here >

3.6. Robustness of risk heterogeneity

Since most of the investment objectives in the two classification schemes show differences between the risk of load and no-load funds, it is instructive to see if controlling for load structure corrects heterogeneous within group risk. To determine if systemic differences in risk between load and no-load funds were the sole cause of heterogeneous within group risk, the sample was partitioned into load and no-load sub samples and one-way ANOVA on betas was repeated for each sub sample. To conduct statistical testing, βs are computed using monthly data over rolling one-year periods for the thirteen-year period. This provides a distribution of βs for each fund. These βs are then compared using One-way ANOVA to test the equality of βs within each investment objective group for each load structure to learn if the average β for all funds within the investment objective group are then equal.

Table 8 presents results of the One-way ANOVA F-test to determine if observed risk differences remain after controlling for classification schemes and load effects. Panels A and B present the results for load and no-load funds respectively. Column one provides the *Wall Street Journal* investment objective and column two is the number of funds comprising the sample. Columns three through seven are the ANOVA F-statistic p-values for the null hypothesis that the risk for investors is homogeneous within the investment objective group. They are provided for the DJIA, S&P 500, CRSP EW, VW, and MSCI indices respectively. Results in column three (Panel A) indicate that for load funds, all four of the testable investment objectives have heterogeneous within group risk at the .01 level from the perspective of investors holding portfolios with characteristics like those of the DJIA. Results in column three (Panel B) indicate that for no-load funds, again, all four of the testable investment objectives have heterogeneous within group risk at the .01 level from the perspective of investors holding portfolios with characteristics like those of the DJIA. Other indices confirm risk heterogeneity within investment objective groups even after controlling for load effects.

<Insert Table 8 about here >

Table 9 presents results of the One-way ANOVA F-test to determine if observed risk differences remain after using the Brown and Goetzmann (1997) classification. The procedure is identical to that above. Panels A and B present the results for load and no-load funds, respectively. Column one provides the Brown and Goetzmann (1997) investment objective and column two is the number of funds comprising the sample. Columns three through seven are the ANOVA F-statistic p-values for the null hypothesis that the risk is homogeneous within the investment objective group. They are provided for the DJIA, S&P 500, CRSP EW, VW, and MSCI indices respectively. Results in column three (Panel A) indicate that for load funds, all four of the investment objectives have heterogeneous within group risk at the .01 level from the perspective of investors holding portfolios with characteristics like those of the DJIA. Results in column three (Panel B) also indicate that for no-load funds, all four of the testable investment objectives have heterogeneous within group risk at the .01 level from the perspective of investors holding portfolios with characteristics like those of the DJIA. Again, results using other indices confirm risk heterogeneity within the investment objective classifications.

<Insert Table 9 about here >

4. Conclusion

The use of investment objectives to proxy risk is common in practice; therefore, it is extremely important to know whether it is an appropriate measure of risk. If investors believe that investment objectives are valid risk proxies, they may compare raw returns of funds within that asset class and select the fund with the highest return. However, if the risks of the funds differ, the capital asset pricing model and efficient market hypothesis would suggest that the investor may be unwittingly selecting the higher risk fund and ending up with lower utility.

I extend the findings of Najand and Prather (1999) to ascertain whether the load structure of the funds may drive their heterogeneous within class risk findings. If both load and no-load fund managers within a given investment objective class face similar constraints, the risk of the risky portfolio that they select should be similar. However, recent literature, (e.g., Capon, Fitzsimons, and Prince (1996), Chevalier and Ellison (1997), Chordia (1996), Goetzmann, Greenwald, and Huberman (1992), Goetzmann and Peles (1997), Gruber (1996), Ippolito (1992), Sirri and Tufano (1998)), suggests that agency problems may cause load and no-load fund managers to hold differing percentages of cash to meet uncertain redemptions. Therefore, it is possible that findings of risk heterogeneity are not due to lacking regulation or inability to properly capture risk. Rather, it may be a logical response by managers attempting to maximize their own utility.

To examine risk, I conduct empirical testing on monthly returns of more than 300 mutual funds over a thirteen-year period. Results suggest that the average risks of load and no-load funds differ statistically. After segmenting the sample into load and no-load funds, I examine the risk homogeneity of funds within investment objective classes using analysis of variance (ANOVA). Results suggest that risk is not homogeneous within investment objective classes and the risks of load and no-load funds generally differ. Moreover, the result is robust with respect to the selected market proxy and investment-objective classification scheme.

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Table 1.
Sample

CDA Investment Objective	Number of Funds
Aggressive Growth (AG)	43
Growth (G)	112
Growth and Income (GI)	66
Balanced (B)	36
Bond and Preferred Stock (BP)	66
Total	323

Note: Column one presents the CDA investment objective classification and the descriptor used for that classification and column two presents the sample size for that investment objective.

Table 2.
Range of Estimated Betas

Investment Objective	Number of Funds	Index (maximum/minimum) DJIA	S&P 500	CRSP EW	CRSP VW	W
AG	43	1.42/ .72	1.50/ .79	1.46/ .70	1.57/ .81	1.14/ .63
G	112	1.17/ .40	1.24/ .45	1.18/ .36	1.29/ .47	.94/.38
GI	66	1.01/ .23	1.04/ .24	.93/ .25	1.06/ .25	.80/ .19
B	36	.92/ .29	.95/ .31	.88/ .30	.99/ .32	.73/ .25
BP	66	.65/ .00	.66/ .00	.67/ .00	.68/ .00	.52/ .00

Note: Column one provides the CDA investment objective and column two lists the number of funds comprising the sample. Columns three through six are the estimated systematic risk measures for domestic investors using the Dow Jones Industrial Average (DJIA), S&P 500, CRSP EW, and CRSP VW indices as market proxies, respectively. Column seven is the estimated systematic risk for globally diversified investors using the MSCI index as a market proxy.

Table 3.
Homogeneity of Systematic Risk within CDA Investment Objective Classes

Investment Objective	Number of Funds	Index (F value)				
		DJIA	S&P 500	CRSP EW	CRSP VW	W
AG	43	2.406**	2.737**	3.135**	2.135**	.506
G	112	3.557**	4.606**	1.094	.995	.758
GI	66	9.703**	13.132**	7.286**	9.962**	2.538**
B	36	7.085**	7.911**	4.752**	.999	1.471*
BP	66	3.314**	2.469**	1.937**	2.585**	2.047**

Note: This table presents results of the one-way ANOVA F-test to determine if risk differences observed in Table 2 are statistically significant or whether they can be attributed to chance. Column one provides the CDA investment objective and column two lists the number of funds comprising the sample. Columns three through six are the ANOVA F-statistics for the tests of the null hypotheses 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 CRSP VW indices respectively. Column seven is the ANOVA F-statistic for the test of the null hypothesis that the risk for globally diversified investors (MSCI) is homogeneous within the investment objective group. Results in column three indicate that all five of the investment objectives have heterogeneous within group risk at the .01 level from the perspective of domestic only investors holding portfolios with characteristics like those of the DJIA. **,* Indicates significance at the .01 and .05 levels, respectively.

Table 4.
Homogeneity of Systematic Risk between Load and No-load Funds

Investment Objective	Total	Number of Funds Load	No-load	βLD	R^2
AG	43	21	22	1.030*	.986
G	112	52	60	1.040*	.991
GI	66	39	27	1.099*	.989
B	36	22	14	1.066*	.972
BP	66	46	20	1.099*	.951

Note: This table presents the results of tests of whether systemic differences in risk exist between load and no-load funds. Column one is the CDA investment objective group. Columns two through four provide the sample size for the total sample, the load fund sample, and the no-load fund sample, respectively. Column five provides the slope estimate generated by regressing the returns of the index of load funds on the index of no-load funds over the 156-month sample period. A beta of one would suggest equal risk whereas a beta with a confidence interval that excludes one would suggest that risk is significantly different between the two groups. The market model below estimates betas:

$$R_{mf,t} - R_{f,t} = \alpha + \beta(R_{M,t} - R_{f,t}) + \varepsilon_t .$$

* Indicates that the .05 confidence interval does not include one.

Table 5.
CDA Systematic Risk Homogeneity after Controlling for Load

Panel A Load Fund Systematic Risk

Investment Objective	Number of Funds	DJIA	Index (p-value) S&P 500	CRSP EW	CRSP VW	W
AG	21	.0022	.0002	.9868	.0004	.1055
G	52	.0000	.3072	.9943	.0000	.0000
GI	39	.0000	.0000	.0389	.0000	.0000
B	22	.0000	.0000	.2760	.0000	.0000
BP	46	.0000	.0025	.0001	.0000	.0000

Panel B No-load Fund Systematic Risk

Investment Objective	Number of Funds	DJIA	Index (p-value) S&P 500	CRSP EW	CRSP VW	W
AG	22	.0004	.0000	.9438	.0000	.0003
G	60	.0000	.0000	.6063	.0000	.4859
GI	27	.0000	.0000	.0000	.0000	.0000
B	14	.0000	.0000	.0161	.0000	.4535
BP	20	.0001	.0001	.0927	.0016	.0011

Note: This table presents results of the one-way ANOVA F-test to determine if risk differences observed in Table 4 remain after controlling for load effects. Panel A presents the results for load funds and Panel B presents the results for no-load funds. Column one provides the CDA 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 tests of the null hypotheses 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 test of the null hypothesis test that the risk for globally diversified investors (MSCI) is homogeneous within the investment objective group.

Table 6.
Homogeneity of CDA Total Risk

Panel A (Load Funds)

Investment Objective	Number of Funds	Minimum Variance	Maximum Variance	Hartley Statistic
AG	21	.0017	.0060	3.4509^{***}
G	52	.0013	.0038	2.8406^{**}
GI	39	.0006	.0023	3.6887^{***}
B	22	.0005	.0022	3.9873^{***}
BP	46	.0002	.0013	7.9669^{***}

Panel B (No-load)

Investment Objective	Number of Funds	Minimum Variance	Maximum Variance	Hartley Statistic
AG	22	.0023	.0049	2.0695^{**}
G	60	.0009	.0033	3.6717^{***}
GI	27	.0003	.0024	8.4641^{***}
B	14	.0004	.0013	3.2105^{***}
BP	20	.0000	.0006	112.4264^{***}

Note: This table presents the results of the Hartley test on the total variance of funds within each of the eight CDA investment objectives. 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. ***, ** Indicates significance at the .01 and .05 levels, respectively.

Table 7.
Homogeneity of Systematic Risk for Alternate Classification Schemes

	Panel A	Homogeneity of Brown & Goetzmann's Systematic Risk			
Investment		Number of Funds			
Objective	Total	Load	No-load	βLD	R^2
G	61	37	24	1.062*	.989
GI	71	35	36	0.958*	.992
I	41	19	22	0.725*	.884
VAL	22	10	12	0.934*	.959

	Panel B	Homogeneity of *Wall Street Journal's* Systematic Risk			
Investment		Number of Funds			
Objective	Total	Load	No-load	βLD	R^2
CAP	26	12	14	1.017	.974
GI	69	37	32	0.980*	.992
GRO	76	40	36	1.103*	.993
SB	28	18	10	0.985	.972

Note: This table presents the results of tests of whether systemic differences in risk exist between load and no-load funds for other classification schemes. Panel A presents the results for Brown & Goetzmann's classification scheme (G=glamour, GI=growth & income, I=income, VAL=value) whereas Panel B presents the results for the *Wall Street Journal's* classification scheme (CAP=capital appreciation, GI=growth & income, G=growth, SB=stock and bond). Column one is the investment objective group. Columns two through four provide the sample size for the total sample, the load fund sample, and the no-load fund sample, respectively. Column five provides the slope estimate generated by regressing the returns of the index of load funds on the index of no-load funds over the 156-month sample period. A beta of one would suggest equal risk whereas a beta with a confidence interval that excludes one would suggest that risk is significantly different between the two groups. The market model below estimates betas:

$$R_{mf,t} - R_{f,t} = \alpha + \beta(R_{M,t} - R_{f,t}) + \varepsilon_t .$$

* Indicates that the .05 confidence interval does not include one.

Table 8.
Load Controlled Homogeneity of Wall Street Journal Risk Classes

Panel A (Load Funds)

Investment Objective	Number of Funds	Index (p-value) DJIA	S&P 500	CRSP EW	CRSP VW	W
GRO	40	.0000	.0000	.4720	.0000	.9957
CAP	12	.0002	.0000	.0000	.0000	.5618
GI	37	.0000	.0000	.0000	.0000	.8117
SB	18	.0000	.0000	.0000	.0000	.1879

Panel B (No-load Funds)

Investment Objective	Number of Funds	Index (p-value) DJIA	S&P 500	CRSP EW	CRSP VW	W
GRO	36	.0000	.0000	.0000	.0000	.0026
CAP	14	.0005	.0000	.0000	.0001	.7610
GI	32	.0000	.0000	.0000	.4715	.0005
SB	10	.0000	.0000	.0000	.4456	.0335

Note: This table presents results of the one-way ANOVA F-test to determine if risk differences observed in Table 7 remain after controlling for load effects. Panel A presents the results for load funds and Panel B presents the results for no-load funds. Column one provides the *Wall Street Journal's* investment objective (CAP=capital appreciation, GI=growth & income, G=growth, SB=stock and bond) and column two is the number of funds comprising the sample. Columns three through six are the ANOVA F-statistic p-values for the tests of the null hypotheses 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 test of the null hypothesis test that the risk for globally diversified investors (MSCI) is homogeneous within the investment objective group.

Table 9.
Load Controlled Homogeneity of Brown and Goetzmann Risk Classes

Panel A (Load Funds)

Investment	Number of	Index (p-value)				
Objective	Funds	DJIA	S&P 500	CRSP EW	CRSP VW	W
G	37	.0000	.0000	.0000	.0000	.9957
VAL	10	.0000	.0000	.0000	.0000	.0628
GI	35	.0024	.0000	.0092	.0001	.9936
I	19	.0000	.0000	.0000	.0000	.0001

Panel B (No-load Funds)

Investment	Number of	Index (p-value)				
Objective	Funds	DJIA	S&P 500	CRSP EW	CRSP VW	W
G	24	.0029	.0000	.0001	.0000	.9908
VAL	12	.0002	.0019	.0000	.0297	.5567
GI	36	.0209	.0009	.0054	.0023	.9737
I	22	.0000	.0000	.0000	.0000	.0000

Note: This table presents results of the one-way ANOVA F-test to determine if risk differences observed in Table 7 remain after controlling for load effects. Panel A presents the results for load funds and Panel B presents the results for no-load funds. Column one provides the Brown and Goetzmann investment objective (G=glamour, GI=growth & income, I=income, VAL=value) and column two is the number of funds comprising the sample. Columns three through six are the ANOVA F-statistic p-values for the tests of the null hypotheses 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 test of the null hypothesis test that the risk for globally diversified investors (MSCI) is homogeneous within the investment objective group.