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Predicting Mutual Fund Performance: A Portfolio Commonality Approach

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ABSTRACT

In order to outperform his peers, a mutual fund manager may decide to invest in stocks that are considerably different from his competitors. By investing in a unique portfolio, the fund manager has a greater chance of either outperforming or underperforming his peers than those managers who invest in a common portfolio (i.e., herding). This study finds some evidence that mutual funds with unique portfolios tend to earn higher returns on an absolute and a risk-adjusted basis, compared to funds that invest in more common portfolios. The results demonstrate some empirical supports for our hypothesis for both six-month and one-year holding periods as well as for growth and growth/income funds. We conjecture these results are consistent with the argument that fund managers investing in uncommon portfolios possess superior stock selection ability. Consequently investing in these undervalued stocks significantly improves their fund returns.

JEL: G0, G15

Keywords: Mutual fund; Performance; Prediction

I. INTRODUCTION

Mutual funds have grown to become one of the most dynamic and successful industries in the country by changing the ways Americans save and invest. Their success is due to buoyant stock and bond markets, new investment products, and savvy marketing. Mutual funds are widely reported to offer the advantages of diversification, high liquidity, and professional management. This last feature (professional management) is of great interest to investors, with individuals spending considerable time sifting through publications in search of those funds with superior track records. With the increased popularity of defined-contribution pension plans during the 1990s, this process has intensified. Individuals are now given the responsibility under their pension plans (e.g., 401(k) and 403(b)) of choosing mutual funds for their employer-sponsored and supplemental retirement plans. The search for mutual funds with successful professional management has intensified, often accompanied by increased confusion on the part of investors.

Obviously investors prefer mutual funds that earn high rates of return to those that offer more mediocre performance. But what does the process look like from the mutual fund portfolio manager's viewpoint? After all, the long-term performance record of mutual fund managers as a group is less than sterling. Since financial markets tend to follow a risk/return tradeoff, one way of increasing the fund's expected return is to accept more systematic risk in the portfolio. Hence, higher expected returns might be achieved by investing in higher beta stocks.

Another potential way of increasing a fund's expected return, as compared to other funds, is to pursue a stock selection strategy that invests in stocks that are considerably different from those of the competition. If a portfolio manager is willing to exert independent thinking and stand out from the rest of the crowd, the fund's return would tend to be different from those funds which are following a "me-too" or crowd psychology.

Specific questions of interest are: To what extent do portfolio managers exert independent thinking in stock selection (or does the herd mentality predominate)? Does a strategy of differentiating the portfolio lead to higher returns? What are the risks of such a strategy? If the strategy is successful, can a mutual fund's attractiveness be ranked by the extent to which its portfolio differs from others in its class?

This paper seeks to answer some of the questions. By using portfolio holding data from 1992/1993 growth/income funds, June 1997 growth/ income funds, and June 1997 growth funds in conjunction with monthly return data, we find some evidence to support the notion that portfolio commonality measures such as SUM and PRODUCT (as defined later) serve as a predictor for growth and growth/income mutual fund performance in our sample periods. In other words, a mutual fund manager investing in a unique portfolio would lead to a significantly higher ex-post risk-adjusted return while a manager investing in a popular portfolio would lead to a relatively lower ex-post risk-adjusted return. We understand our evidence is limited to the choice of mutual fund objectives and time period of portfolio holdings we employ in our analysis.

The organization of the paper is as follows. Section II provides a brief literature review. Section III discusses the portfolio commonality hypothesis and data, while commonality classification variables and performance measures are defined in Section IV. Section V presents the empirical findings and Section VI concludes the paper.

II. LITERATURE REVIEW

There have been extensive studies on mutual fund performance with mixed results. On one side, some studies (Jensen, 1967; Friend, Brown and Vickers, 1962; Treyner and Mazuy, 1966; Sharpe, 1966; Shawky, 1982; Rahman, Fabozzi and Lee, 1991; Christopherson and Turner, 1991) find index-like or below-index performance. On the other hand, several studies (Friend, Blume and Crockett, 1970; Carlson, 1970; McDonald, 1974; and Mains, 1977; Kon and Jen, 1979; Grinblatt and Titman, 1993) provide evidence of superior expertise on the part of mutual fund managers. They show that mutual fund managers have the ability to deliver superior performance.

After examining the voluminous literature, Ippolito (1993) concludes that results of statistical studies of mutual fund returns, as a group, are generally consistent with one hypothesis: that mutual funds' risk-adjusted performance is statistically indistinguishable from that of index funds, on a net of expenses basis. Another aspect of mutual fund research focuses on the investment behavior of mutual fund managers and their relationships to fund performance. One mutual fund management behavior is herding. Herding refers to the behavior of different investors buying and selling the same stocks within the same period (e.g. same quarter). Previous studies have shown that investors exhibit herd-like behavior. Friend et al (1970) argue that some mutual funds have a tendency to follow the investment choices of their more successful counterparts. This kind of similarity of investment behavior is a result of mutual monitoring of performance among fund managers (Lakonishok, Shleifer and Vishny, 1992) and the relative performance benchmark used in compensation contracts offered to the fund managers (Maug and Naik, 1995).

As for the relationship between herding and the performance of funds as a group, Scharfstein and Stein (1990) suggest that if the herding behavior is due to the tendency of the informed portfolio managers to pick underpriced stocks, these funds should realize good future performances. In their study of mutual fund behavior, Grinblatt, Titman and Wermers (1995) show that performance of funds as a group is significantly correlated with the tendency of a fund to herd. However, this correlation would probably disappear when the tendency to buy past winners is accounted for, thus implying that funds tend to buy past winners in order to show good performance, with herding in past winners occurring as a result.

Wermers (1998) investigates the relationship between mutual fund herding and stock price effects. He finds little herding by mutual funds in an average-size stock. However, the level of herding is more intense in small stocks and among growth mutual funds. Nofsinger and Sias (1999) examine herding and feedback trading by institutional and individual investors. They find that there are strong positive correlation between changes in institutional ownership and returns measured over the same period. Hence, there is herding-like behavior for institutional investors. Chevalier and Ellison (1999), in a study of the mutual fund manager labor market, find younger mutual fund managers hold less unsystematic risk assets and more conventional portfolios. The results of Chevalier and Ellison suggest that, at least for some managers, there is herding-like behavior.

The studies on neglected firms provide related literature for this research. Bauman (1964, 1965) first documents that there are neglected firm effects. Essentially, neglected firms provide better performance. Arbel et al. (1983) also suggest that there is a neglected firm effect. Arbel et al. find that the risk-adjusted returns of neglected firms outperform those of firms that are widely followed by institutional investors. In similar studies within a multifactor asset pricing model, Dowen and Bauman (1986 a, b) also document the existence of a neglected firm effect.

In conclusion, the finance literature has documented some degree of herding behavior among mutual funds. In this study, we examine the relationship between the performance of individual funds and their degree of herding. We first introduce a ranking system of portfolio commonality (i.e., degree of herding). Then we examine the relationship between performance of mutual funds and their commonality ranking in both six-month and one-year periods.

III. HYPOTHESIS AND DATA

A. Hypothesis

In the investment arena, "good" or "bad" performance is a relative matter. Since mutual funds are classified by objectives, the average performance of other mutual funds with the same objective frequently serves as the benchmark for evaluation purposes. If the manager loses 2 percent while the benchmark loses 5 percent, the manager has outperformed his peers. Therefore, if a manager wants to make sure that his mutual fund will not underperform other funds within the same group, he can attempt to mimic the portfolios of his major competitors. This action, in essence, partially indexes the fund to the benchmark and leads to average performance (relative to the rest of the group). The old adage "there is safety in numbers" may apply to many in the mutual fund arena. In fact, "risk-averse" managers who are concerned about their reputations in the mutual fund industry often mimic the investment decisions of other managers. This sort of herding behavior among professional fund managers is well documented in the finance literature.

On the other hand, if a manager decides to invest in stocks that are not part of the holdings of other funds (with the same investment objective), the fund is more likely to either outperform or underperform the benchmark of the group. The deviation from the peer group return will be much larger than that of the herding strategy. This is obviously a (personal) "high risk-high expected return" position. Under the condition that investors are less likely to fire managers if they all have the same performance, even though the collective performance is mediocre, some managers have little incentive to take the additional risk to invest in unique stocks (i.e., stocks that are not being held by other funds). Those who do so must earn a higher rate of return to justify the additional risk (both portfolio risk and "personal risk") and research cost.

A risk-averse fund manager seeks a higher expected rate of return in order to accept the higher investment risk involved. Obviously, investing in a unique portfolio (i.e., the opposite of herding) increases the risk of deviating from the benchmark (mean return of the funds within the same investment objective), thus a fund manager would require a higher expected return to compensate for this risk of "unherding". Consequently, unherding managers should seek a higher expected return than their herding peers.

If the manager makes wise decisions, he will be rewarded, either by receiving financial compensation (bonus, raise, etc.) or by using his performance record to move to a higher paid position in another firm. This scenario is clearly the high risk-high expected return option. On the other hand, if he makes "bad" decisions, he will be penalized by missing possible bonuses, being unable to change firms, and possibly even being fired. This risk is avoided by taking a low risk-low expected return option.

To what extent do fund managers differentiate their portfolios from their peer group? Is independent thinking of fund managers rewarded by improved performance? We argue that managers as a group are willing to stand out from the crowd and pursues an independent course are more likely to possess superior stock selection ability. From the standpoint of risk-averse behavior, unless the wise manager is very confident about his forecasts on stock performance, he would not be inclined to invest in a unique stock portfolio. Thus the probability of a successful (more profitable) unique portfolio may be higher than that of an unsuccessful (less profitable) unique portfolio.

Specifically, this paper examines whether mutual funds with unique portfolios (i.e., differentiated portfolios) earn higher rates of return than funds with considerable commonality in their investments. The paper develops a ranking system for mutual funds based on the extent to which their portfolio holdings overlap (i.e., the extent to which they hold the same securities). The results from the ranking system are then tested against various measures of the funds' performance over holding periods of six and twelve months to see if portfolio differentiation is a viable strategy.

B. Data

We collect cross-sectional data from *Morningstar* between October 1992 and July 1993 for our initial analysis in this study. The choice of issues and dates is limited by the printing cycle of *Morningstar* reports. The advantage of using *Morningstar* data is that it provides portfolio holding, rates of return and beta in one source[1]. It helps avoid the problem of non-synchronous data. Owing to the infrequent reporting of the same mutual funds, we are not able to use time series analysis as the sample of mutual funds varies substantially when the time period is too long. Finally, in order to maximize our sample size, we choose growth-income funds because they are the largest group reported by *Morningstar*.

The initial data for this paper are taken from three consecutive editions (beginning October 1992) of *Morningstar Mutual Funds*. The editions contain data of 119 funds with the same growth-income investment objective. Performance information pertaining to future returns is collected from subsequent editions of the publication. To be eligible for the sample, first, the fund must have a stated investment objective of growth-income. Second, the fund must have been covered by three editions of *Morningstar Mutual Funds* (issues of October 1992; February or March 1993; and July

1993). Since nineteen funds discontinued in subsequent editions after October 1992, they are eliminated from our study.

Third, the fund is required to have active investment strategies with a minimum of thirty equity holdings in their portfolios. Based on this criterion, four indexed funds are dropped. Another one is taken out from the sample because it invests solely in other mutual funds. Seven additional funds are eliminated for having less than 30 portfolio holdings. Finally, the holding periods for return data in *Morningstar* do not always have the same number of days. Nine additional funds are dropped from the study for having returns information for which the holding periods vary too many days from the 6-month or 1-year holding periods studied. These adjustments leave a total of 79 funds included in the sample with the same objective and active investment strategies.[2] In order to further strengthen our tests, we also include a second data set from *Morningstar*'s CD ROM data for the portfolio holding as of June 1997 for both growth and growth income funds.

IV. CLASSIFICATION VARIABLES AND PERFORMANCE MEASURES

A. Classification Variables

We employ four different classification methods to measure portfolio commonality of individual funds (herding intensity). These four measures reflect how unique or common the stock portfolio of each mutual fund is. The entire database of equity holdings held by the 79 mutual funds is initially sorted alphabetically by company names. A *frequency rating* for each security is then determined by counting and recording the total number of funds investing in each stock. For example, if Phillip Morris is held by 48 of the 79 funds, Phillip Morris receives a frequency rating of 48. The database is then re-sorted by mutual fund name. We then come up with the following classification variables:

a. First Classification Variable:

$$SUM_j = \sum_{i=1}^{30} f_{ij}$$

where f_{ij} = frequency rating of i^{th} stock in the j^{th} mutual fund

The first ranking method is developed by simply summing the frequency ratings of the 30 securities, with the greatest frequencies, held by a fund (e.g., 48 for Phillip Morris, 37 for IBM, etc.). This value is referred to as SUM. Mutual funds with a less common (or unique) portfolio have smaller SUM values and funds with a more common portfolio have larger SUM values.

b. Second Classification Variable:

$$PRODUCT_j = \sum_{i=1}^{30} f_{ij} * w_{ij}$$

where $w_{ij} = V_{ij} / V_j$
V_{ij} = market value of i^{th} stock in j^{th} fund
V_j = total market value of jth fund

Although several funds may invest in the same security, the percentage of net assets devoted to a particular security may vary widely. The percentage of assets allocated to a particular security should measure the fund manager's conviction that the security is attractive. To adjust for this preference, each security's frequency rating is multiplied by the corresponding percentage of net assets allocated to that security. This adjusted rating is then summed for each fund, and the results are used to form a portfolio commonality ranking defined as PRODUCT. Therefore, PRODUCT is a weighted average of the frequency ratings, using the percentage of assets as the weighting factor. Similar to SUM, a less common (unique) portfolio would have a smaller PRODUCT value and a more common portfolio would have a larger PRODUCT value.

c. *Third Classification Variable*:

$$TILT_j = \sum_{k=1}^{10} (x_{jk} - \bar{x}_k)^2$$

where x_{jk} = k^{th} sector weight in j^{th} fund

$\bar{x}_k$ = mean value of sector weights for all funds in k^{th} sector

To capture a fund's possible tilt toward particular sectors, the mutual funds' holdings are divided into ten categories:

1.	natural resources	6.	industrial production
2.	consumer durable	7.	non-durable
3.	retail trade	8.	services
4.	utilities	9.	transportation
5.	finance	10.	multi-industry

These ten categories follow *Morningstar*'s industry classification for stocks. The percentage of each fund's assets invested in various sectors (i.e., its weighting) for the specific category is recorded. This information is then used to determine whether the fund is tilting the portfolio toward a particular sector (i.e., placing emphasis on certain sectors, or avoiding specific categories). The sector weighting information is used in the following way:

1. A mean value of the 79 funds in the sample is first calculated for each sector category.
2. The deviation (i.e., the difference) between the funds's weighting in that category and the sector category mean is then determined.
3. The squared deviations are summed for each fund.

This results in a ranking for each mutual fund based on its commonality to other funds' sector holdings. This variable is referred to as TILT. A bigger number signifies that the fund places a higher emphasis on certain categories than its peers do and consciously tilts the portfolio in that direction.

d. Fourth Classification Variable:

$$\text{INTERVAL}_j = \text{pos}(x_{jk} - \bar{x}_k) - \text{neg}(x_{jk} - \bar{x}_k)$$

where $\text{pos}(x_{jk} - \bar{x}_k)$ = frequency of $(x_{jk} - \bar{x}_k) > 0$

$\text{neg}(x_{jk} - \bar{x}_k)$ = frequency of $(x_{jk} - \bar{x}_k) < 0$

A similar ranking system examines whether the deviation from the mean for a category is positive or negative. For each of the ten sectors, the fund's sector weighting is compared to the mean sector weighting, resulting in a positive (above the mean) or negative (below the mean) value. A commonality-ranking variable defined as INTERVAL (for the interval scale) is then derived by subtracting the number of negative deviations from the number of positive deviations.

For instance, if a fund's portfolio is above the mean in 7 sectors and below in 3, the INTERVAL value would be +4. A value greater than zero (e.g. +1, +2, +3) indicates that the number of overinvested sectors exceeds the number of underinvested sectors. A value of zero means the number of positive and negative deviations from the mean is equal. A value less than zero (e.g. -1, -2, -3) indicates that the number of underinvested sectors exceeds the number of overinvested sectors.

The SUM and PRODUCT variables focus on individual stock selection (a bottom-up approach to investing), while the TILT and INTERVAL variables capture a top-down approach of mutual fund investing strategy. Mutual funds may tilt their portfolios toward the most attractive sectors of the economy. In other words, the fund manager begins with a forecast of future economic growth, and then tries to position the fund in those industries which will profit the most in the industry cycles. Therefore, TILT and INTERVAL commonality rankings measure the fund managers' tendency to focus on particular industries (or sectors).

B. Performance Measures

To measure performance, we use four different measures of return. Two of them are simple absolute rate of returns over a particular holding period (calculated by *Morningstar*). The remaining two utilize Treynor's ratio to adjust for the market risk of a particular portfolio. Specifically, the four measures are:

1. The funds' absolute (non-risk-adjusted) total returns for the relevant six-month holding period.
2. The funds' absolute (non-risk-adjusted) total returns for the relevant twelve-month holding period.

3. The Treynor measures of the funds (risk-adjusted returns) for the relevant six-month holding period.
4. The Treynor measures of the funds (risk-adjusted returns) for the relevant twelve-month holding period.

Data on total return and beta[3] are taken from subsequent editions (February or March 1993, and July 1993) of *Morningstar Mutual Funds* after October 1992. For the 1997 data, CDROM files from *Morningstar* are used. For Treynor's return/risk ratio, the applicable risk-free rate of return (6-month or 1-year U.S. Treasury bill rate) is subtracted from the total return for each time period (to determine the portfolio's risk premium). This value is then divided by the beta for each fund.

As CDROM data are not available during 1993 when we start working on the project, the 1992/1993 data are collected from hard copies of *Morningstar* reports. Thus matching the returns with the portfolio holding data is a difficult task because the release of portfolio holding data is relatively infrequent. Consequently we choose one-year and six-month returns as our performance measures. In 1997, we realize that the data is available in CDROM format. Unfortunately, the earliest year that *Morningstar* still has inventory is 1997. Therefore, we pick June 1997 as our portfolio holding date for additional analysis.

As we hypothesize that a smaller SUM, PRODUCT, and TILT would lead to a higher expected return, we use a one-tail t-test to determine the statistical significance of the differences in returns of the sub-samples. For INTERVAL, we use a two-tail t-test since a unique portfolio can have either more overinvesting (i.e., a positive value for INTERVAL) or more underinvesting sectors (i.e., a negative value for INTERVAL).

V. FINDINGS

Based on the 1992/1993 data, we sort the 79 growth-income funds by each of the four measures of portfolio commonality (SUM, PRODUCT, TILT, and INTERVAL), and subdivide each sample approximately in half into two groups (unique and common). There are 39 and 40 funds in unique and common groups, respectively. The characteristics of the overall sample, the unique and common groups, and the two-sample t-test results are reported in Table 1.

Table 1
Descriptive statistics of classification variables

SUM:	The sum of the frequency ratings of the top 30 stocks held by the funds.
PRODUCT:	The weighted average of the frequency rating, using the percentage of assets as the weighting factor.
TILT:	The sum of the squared deviations between a fund's weighting in a sector and the sector mean.
INTERVAL:	The number of positive deviations from the sector mean minus the number of negative deviations.

Classifier	*Overall*	*Unique Group*	*Common Group*	*Difference*
SUM Mean	326.43	240.30	414.77	174.47
Std. Dev.	110.56	63.79	71.38	t = 11.445
Range	115 to 609	115 to 335	336 to 609	p = 0.000 **
PRODUCT Mean	636.89	440.63	838.18	397.55
Std. Dev.	245.13	145.62	139.44	t = 12.395
Range	139 to 1,232	139 to 660	669 to 1,232	p = 0.000 **
TILT Mean	1.39	0.86	1.93	1.07
Std. Dev.	0.75	0.20	0.72	t = 8.920
Range	0.44 to 4.53	0.44 to 1.23	1.24 to 4.53	p = 0.000 **
INTERVAL Mean	0.76	2.40	0.92	3.32
Std. Dev.	2.20	1.52	1.36	t = 10.246
Range	-6 to 4	-6 to 0	0 to 4	p = 0.000 **

** Significant at 0.05 level
 * Significant at 0.10 level

C. Two-sample t-tests

To examine if there exists a significant difference between the ex-post returns of funds with more unique portfolios and funds with more common portfolios, we perform two-sample t-tests on the mean returns of each pair of subgroups classified by the four commonality measures. The tests are repeated for 6-month and 1-year absolute and risk-adjusted returns of the two groups. The detailed results are reported in Table 2 with respect to the four different rates of returns while the findings are summarized in Panels A and B of Table 3.

Table 2
Average return for various holding periods and comparisons

SUM: The sum of the frequency ratings of the top 30 stocks held by the funds.
PRODUCT: The weighted average of the frequency rating, using the percentage of assets as the weighting factor.

	1-Year Absolute Return		1-Year Risk-Adjusted Return		6-Month Absolute Return		6-Month Risk-Adjusted Return	
	Unique Group	*Common Group*	*Unique Group*	*Common Group*	*Unique Group*	*Common Group*	*Unique Group*	*Common Group*
1992/1993 Growth/Income (N=79)								
Two-Group Comparison (N (Unique) = 39, N (Common) = 40)								
SUM	14.02%	11.86%	12.50%	9.93%	6.54%	5.08%	5.62%	3.87%
PRODUCT	14.12%	11.57%	12.75%	9.67%	6.55%	5.07%	5.51%	3.98%
Three-Group Comparison (N (Unique) = 26, N (Common) = 26)								
SUM	14.80%	11.84%	13.33%	9.82%	6.75%	4.70%	5.78%	3.41%
PRODUCT	13.27%	10.44%	11.85%	8.15%	6.10%	4.56%	5.11%	3.42%
1997 Growth (N=73)								
Two-Group Comparison (N (Unique) = 36, N (Common) = 37)								
SUM	23.02%	26.86%	3.50%	1.42%	10.43%	9.53%	8.10%	6.48%
PRODUCT	23.80%	26.11%	3.83%	1.10%	10.79%	9.18%	8.46%	6.12%
Three-Group Comparison (N (Unique) = 24, N (Common) = 24)								
SUM	22.69%	29.35%	4.63%	1.81%	11.33%	10.16%	9.10%	6.96%
PRODUCT	23.16%	27.93%	4.48%	1.18%	11.23%	9.25%	9.01%	6.18%
1997 Growth/Income								
Two-Group Comparison (N (Unique) = 30, N (Common) = 30)								
SUM	75.11%	86.50%	47.30%	35.47%	38.94%	39.99%	42.78%	38.92%
PRODUCT	75.47%	86.15%	48.39%	34.38%	39.96%	39.57%	43.54%	38.16%
Three-Group Comparison (N (Unique) = 20, N (Common) = 20)								
SUM	76.36%	86.90%	50.71%	35.37%	41.20%	39.78%	45.15%	38.75%
PRODUCT	72.75%	87.96%	50.38%	33.72%	38.87%	39.54%	43.66%	37.78%

Table 3
Panel A. Statistical results relating to SUM variable

SUM: The sum of the frequency ratings of the top 30 stocks held by the funds.

	Difference in 1-Year Absolute Return Between Unique & Common Group	Difference in 1-Year Risk-Adjusted Return Between Unique & Common Group	Difference in 6-Month Absolute Return Between Unique & Common Group	Difference in 6-Month Risk-Adjusted Return Between Unique & Common Group
Mean Tests	Mean Return (Sig)[Btstrp Sig]			
Two-Group Comparison				
1992 / 1993 Data	2.16%(a)[a]	2.57%(a)[a]	1.46%(b)[b]	1.75%(b)[b]
1997 Growth Data	-3.84%(a)[a]	2.08%(a)[a]	0.90%	1.62%(b)[b]
1997 Growth/Income Data	-11.39 %(a)[a]	11.83%(a)[b]	-1.05%	3.86
Three-Group Comparison				
1992/1993 Data	2.96%(a)[a]	3.51%(a)[a]	2.05%(b)[b]	2.37%(a)[a]
1997 Growth Data	-6.66%(a)[a]	2.82%(b)[a]	1.17%	2.14%(b)[a]
1997 Growth / Income Data	-10.64%(a)[a]	15.34%(a)[a]	1.42%	6.40%(a)[a]
Regression Analysis	Regression Coefficient			
1992 /1993 Data	-0.0006	-0.0011	-0.0010	-0.0020
1997 Growth Data	0.0091	0.0073	-0.0011	-0.0033
1997 Growth / Income Data	0.0171	0.0157	-0.0003	-0.0015

(a) is significant at 5% level using traditional t-statistics.
[a] is significant at 5% level using bootstrap model.
(b) is significant at 10% level using traditional t-statistics.
[b] is significant at 10% level using bootstrap model.

Table 3 (continued)
Panel B. Statistical results relating to PRODUCT variable

PRODUCT: The weighted average of the frequency rating, using the percentage of assets as the weighting factor.

	Difference in 1-Year Absolute Return Between Unique & Common Group	Difference in 1-Year Risk-Adjusted Return Between Unique & Common Group	Difference in 6-Month Absolute Return Between Unique & Common Group	Difference in 6-Month Risk-Adjusted Return Between Unique & Common Group
Mean Tests	Mean Return(Sig)[Btstrp Sig]			
Two-Group Comparison				
1992 / 1993 Data	2.55%(a)[a]	3.08%(a)[a]	1.48%(b)[b]	1.53%(b)[b]
1997 Growth Data	-2.31%(a)[a]	2.73%(a)[a]	1.61%(b)[b]	2.34%(a)[a]
1997 Growth/Income Data	-10.68%(a)[a]	14.01%(a)[a]	-0.21%	5.38(a)[a]
Three-Group Comparison				
1992/1993 Data	2.83%(a)[a]	3.70%(a)[a]	1.54%	1.69%
1997 Growth Data	-4.77%(a)[a]	3.30%(a)[a]	1.98%(b)[b]	2.33%(a)[a]
1997 Growth / Income Data	-15.21%(a)[a]	16.66%(a)[b]	-0.68%	5.88%(b)[b]
Regression Analysis	Regression Coefficient			
1992 /1993 Data	-0.0073(b)	-0.0075(b)	-0.0041	-0.0039
1997 Growth Data	0.0037	0.0030	-0.0005	-0.0003
1997 Growth / Income Data	0.0096	0.0157	-0.0059	-0.0068

(a) is significant at 5% level using traditional t-statistics.
[a] is significant at 5% level using bootstrap model.
(b) is significant at 10% level using traditional t-statistics.
[b] is significant at 10% level using bootstrap model.

Both the absolute and risk-adjusted one-year returns are significantly different for the two groups of funds at the 0.05 level, when using the SUM and PRODUCT commonality measures to classify the funds. For a six-month holding period, both absolute and risk-adjusted returns are statistically different from zero at the 0.1 level. More specifically, the "unique group" which is made up of mutual funds that tend to invest in unique portfolios of stocks earns a significantly higher rate of ex-post return (2 to 3% annually) than the "common group" which invests in similar portfolios of stocks. This evidence of better performance for independent thinking is found on both an absolute and a risk-adjusted basis, and for both six-month and one-year holding periods.

However, as indicated in Appendix 1, the returns for pairs of groups classified by the TILT and INTERVAL measures are not statistically and significantly different from zero. As these two variables measure the extent of commonality in mutual fund portfolios in terms of investment in industry sectors, the results show that there does not appear to be a strong relationship between the commonality of sector weightings and future performance. In other words, even though some mutual fund managers may focus on some industry sectors of the economy and tilt their portfolios toward these common sectors, they are not able to achieve higher ex-post returns than those who do not concentrate on these certain industry sectors. Nevertheless, it should be noted that these results only indicate that there is no significant difference in ex-post returns among mutual funds that are more concentrated on some common sectors and those that are less concentrated on these common sectors. It does not imply that tilting (concentration on particular industry sectors) is not a profitable strategy.

D. Robustness Tests

To make sure that our results are robust to the ways we divide the sample funds, we repeat the tests with other groupings of our sample mutual funds. In particular, we divide the universe of funds into three equal groups, and then compare the highest group of commonality with the lowest group (i.e., the top one-third funds with the lowest one-third). The results are indeed consistent with our earlier findings[4]. The results for the two-sample t-tests for the four different rates of ex-post return measures and commonality groupings are summarized in Panels A and B of Table 3 while the mean returns for each sub-group are reported in Table 2.

To further investigate the robustness of our two-sample t-tests with respect to different types of mutual funds in different time periods, we apply the same two-sample t-tests to growth funds and growth-income funds with June 1997 portfolio holding data. To focus on the variables and performance measures with significant results in our earlier analysis, we provide the same nominal and risk-adjusted return comparisons by SUM and PRODUCT for these additional data. The results are in Tables 2 and 3.

For the 1997 data, the results are similar but not as strong. The 1-year absolute return statistics for both growth and growth-income samples show that the common groups earn higher absolute return than the unique groups. However, when we examine the risk-adjusted return statistics, both fund objectives show that unique groups experience higher returns than the common groups, supporting our hypothesis that unique portfolios measured by SUM and PRODUCT perform better. These results also demonstrate the importance of using risk-adjusted performance to evaluate mutual funds. Otherwise, the conclusion can be totally opposite.

For the 1997 6-month returns, the results follow closely with the 1992/1993 data. Both the growth and growth-income samples show a significantly higher 6-month risk-adjusted return for the unique portfolios than the common portfolios measured by both SUM and PRODUCT. As indicated in these tables, the unique group often outperforms the common group. Hence, our hypothesis that unique group delivers a better performance than the common group is also partially supported by the 1997 data with respect to growth funds and growth-income funds under both two-group and three-group comparisons.

It is possible that due to the herding behavior of mutual fund managers, the fund ex-post returns of unique and common groups may not be independent, and identically and normally distributed. Thus the traditional p-values may be biased[6]. To further examine the robustness of our results, we also use Efron's (1979) bootstrap method to compute the level of significance for the two-group and three-group comparisons. Essentially, for each of the return statistics, we randomly scramble the return observations. For the two-group comparison, we put the first half in one group, and second half in the other. We then apply the two-sample t-test and record the corresponding t-statistic. This procedure is repeated 1,000 times and produces an empirical bootstrapping sampling distribution. Then, the modified p-values are determined from the empirical bootstrapping sampling distribution.

Similar procedures are applied to the three-group comparison to produce new p-values. The two-sample t-test results with p-values from empirical bootstrapping distributions of the two-group and three-group comparisons are used to examine the level of significance (as reported in the squared bracket in Panels A and B of Table 3 respectively). The results are qualitatively the same. That is, using the SUM and PRODUCT classification variables and under the risk-adjusted return basis, the unique group delivers better performance than the common group.

E. Regression Analysis

To test the relationship between performance and the SUM and PRODUCT variables, we conduct a multiple regression analysis with the inclusion of beta in the test. Furthermore, to control possible heteroskedasticity across different mutual funds, we employ White's (1980) general heteroskedasticity correction. In other words, our t-statistics for our regression coefficients would be based on White's heteroscedastically-consistent standard errors. Table 3 Panels A and B report the key figures for SUM and PRODUCT while Appendixes 2 and 3 show the entire regression result. In both data sets, no heteroskedasticity is found in any regression.

Consistent with the two-group and three-group comparisons, the variable PRODUCT is significantly negative in two out of four regression equations for the 1992/1993 data. That is, after controlling for the systematic risk of mutual funds, the more unique mutual fund (with a smaller PRODUCT measure) delivers a better ex-post return. However, the variable SUM is not statistically significant in any equations. This may be because SUM and PRODUCT are highly correlated. Indeed, in Appendix 4 where the correlation coefficients among the four classification variables and beta are reported, the correlation coefficient between SUM and PRODUCT is 0.68 which is the highest among all. Overall speaking, the two-sample t-test shows that SUM and PRODUCT are stand-alone predictors of fund's return. On the other hand, the regression analysis controls for other variables and examines if these two variables explain funds' return in a multivariate context. Thus, an insignificant result from regression analysis for the 1997 data should not affect our interpretation of the two-sample t-test findings.

F. Wilcoxon Signed-Ranks Test

Do our findings have relevance for individual investors who want to select mutual funds with unique portfolios? Do these mutual funds' portfolio characteristics stay unchanging over time? We hypothesize that if mutual fund managers employ the high risk-high return strategy and pursue very different stocks in their portfolios, there will exist considerable persistence in the uniqueness of these mutual funds portfolios. That is, managers who choose to invest with independent thinking and analyses should pursue unique portfolios over a long course of time.

To examine this issue, we conduct a Wilcoxon Signed-Ranks test. The procedure tests for upward and downward movement in the rankings. First, we rank the 79 funds from the most unique portfolio to the least unique one. Then, we examine if the funds in the upper third of the group (i.e., 26 funds) tend to move down in the rankings in future periods of time (i.e., comparing the portfolio holdings in October 1992 issue with those in the February 1993 issue). Based on the z-values, there is no significant movement at the 0.05 level at least over this short period of time[7]. The results suggest that mutual funds with unique portfolios tend to retain that characteristic over time.

VI. SUMMARY

From a career's standpoint, the easy and low-risk strategy for a fund manager is to blend in with the other funds in the industry and not to deviate too far from the norm. If the stock investments go sour, the manager's fund will fall about as much as his peers and the manager will not be viewed as underperforming. If the stock portfolio wins big, the mutual funds can still boast about its high rate of return, though it is not significantly above his peers.

However, managers who possess superior stock selection ability may be willing to stand out from the crowd and pursue an independent course. Therefore, they may choose to exert independent thinking to invest in stocks that are considerably different from those of the competitors in order to have a chance to beat the peers. If a portfolio manager follows this kind of strategy, there is a bigger chance for the fund's ex-post return to be different from those funds which are following a crowd mentality or herding. Thus this strategy will place the managers' career on a high-risk path. This paper examines to what extent mutual fund managers pursue unique portfolios, and whether such a strategy of differentiating the portfolio leads to higher ex-post returns. The results suggest that independent thinking on the part of mutual fund managers is associated with superior risk-adjusted performance. Mutual funds with unique portfolios tend to earn higher ex-post risk-adjusted returns as opposed to managers who follow the herd instinct and construct a "me-too" type of portfolio.

The findings hold for both six-month and one-year holding periods, on an absolute and a risk-adjusted basis. This unique portfolio strategy leads to higher ex-post returns and possibly better career opportunities for the mutual fund managers personally, and thus provides motivation for them to pursue unique portfolios through time. We further show that since such mutual fund managers tend to be persistent in constructing unique portfolios, the commonality approach discussed in this paper may provide an effective method in picking superior mutual funds in general. We conjecture these results are consistent with the argument that fund managers as a group, who invest in uncommon portfolios, possess superior stock selection ability. Consequently investing in these undervalued stocks significantly improves their fund returns. However, we understand that due to the limited time period and number of fund objectives we examine, it is possible that our results can be sample specific and there exist cases when unique portfolios may not earn higher ex-post returns. Future research on a more comprehensive data set is needed to conclude if such a unique portfolio strategy can always bring in higher ex-post returns.

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FOOTNOTES

1. Moody's Manual and Wiesenberger Investment Services Manual also report mutual fund portfolio holdings. However, Morningstar provides more frequent updates and other accompanying mutual fund information in more details.
2. Some mutual fund studies focus on the impact of survivorship bias (e.g., Malkiel, 1995; Brown and Goetzmann, 1995). In our case, we collect our return data from the data disk or hard copies published within the same year instead of using a comprehensive database produced at a much later time. Therefore, our data sources capture all existing (including surviving and non-surviving) mutual funds during that time. As our paper tests a methodology in selecting good performers and does not draw implications from a long-term time series data, the survivorship bias should not be serious. In essence, we examine only a snapshot of mutual fund portfolio holdings for a short cross-sectional period (1992-93 and 1997), the survivorship bias, if any, should be small. For a significant impact of survivorship bias, the time span for fund data has to be much longer.
3. The total return is calculated by taking the change in net asset value, reinvesting all income and capital-gains distributions during the period (plus any other miscellaneous distributions), and dividing by the starting net asset value. These returns are not adjusted for sales charges (i.e., front- and back-end loads, redemption fees), but they do account for management fees, 12b-1 fees, and other costs automatically taken out of fund assets. Beta is calculated using a least-squared regression of the fund's excess total returns, as compared with the monthly total return of the S&P 500 Index. The regression is done with figures from the trailing 36-month period.

4. We also divide the universe into four equal groups as a further test. Results are consistent with those of the two- and three-subgroup tests.
5. In 1993 when we first start working on the project, CDROM data are not yet available. Thus 1992/1993 data are collected from hard copies of *Morningstar* reports. As we are required to revise the paper with more recent data, we realize that data is available in CDROM format. Unfortunately, the earliest year that *Morningstar* still has inventory is 1997. Therefore, we pick June 1997 as our portfolio holding date for additional analysis. Owing to the infrequent releases of both return and portfolio holding data in earlier years, matching the returns with the portfolio holding data is a difficult task. Consequently we choose 1-year and 6-month returns as our performance measures for the 1992/1993 data. As for data in 1997, we employ the same return measures for consistency. Finally, since TILT and INTERVAL do not show any significant results for the 1992/1993 data, we concentrate our effort on SUM and PRODUCT for the additional analysis.
6. Thank you for an anonymous referee for raising this point.
7. To conserve space, the results are not reported in this paper, but are available upon request.

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APPENDIX 1

Average return for various holding periods and comparisons

TILT: The sum of the squared deviations between a fund's weighting in a sector and the sector mean.

INTERVAL: The number of positive deviations from the sector mean minus the number of negative deviations.

	1-Year Absolute Return		1-Year Risk-Adjusted Return		6-Month Absolute Return		6-Month Risk-Adjusted Return	
	Unique Group	*Common Group*	*Unique Group*	*Common Group*	*Unique Group*	*Common Group*	*Unique Group*	*Common Group*
1992/1993 Growth/Income								
Two-Group Comparison								
TILT	13.64%	12.26%	11.59%	10.86%	5.89%	5.74%	4.90%	4.90%
INTERVAL	12.42%	13.50%	11.28%	11.18%	5.33%	6.32%	4.46%	5.06%
Three-Group Comparison								
TILT	13.60%	13.08%	11.40%	11.97%	5.64%	5.87%	4.21%	5.08%
INTERVAL	12.27%	13.90%	11.62%	11.34%	5.65%	6.26%	5.00%	4.75%

Note: Since all the mean returns for two-group and three-group comparison are not significantly different from each other, the t-value and p-values are not reported here.

APPENDIX 2

Regression analysis of mutual fund returns with portfolio holding for 1992/1993 growth/income data

Frequency rating: The total number of sample mutual funds investing in a given security.
SUM: The sum of the frequency ratings of the top 30 stocks held by the funds.
PRODUCT: The weighted average of the frequency rating, using the percentage of assets as the weighting factor.

	1-Year Absolute Return	1-Year Risk-Adjusted Return	6-Month Absolute Return	6-Month Risk-Adjusted Return
Constant	10.8237 (2.72)***	22.3400 (4.67)***	2.6736 (0.78)	6.8677 (1.74)*
SUM	-0.0006 (-0.09)	-0.0011 (-0.14)	-0.0010 (-0.17)	-0.0020 (-0.30)
PRODUCT	-0.0073 (-2.34)**	-0.0075 (-2.06)**	-0.0041 (-1.51)	-0.0039 (-1.27)
BETA	7.8725 (1.90)*	-6.7102 (-1.38)	6.8517 (1.91)*	1.1755 (0.29)
Adjusted R^2	0.1171	0.0995	0.0593	0.0146
F	4.45**	3.87**	2.64*	1.39
White's General Heteroskedasticity Test	13.79	13.64	12.72	12.49

*** Significant at the 0.01 level
** Significant at the 0.05 level
* Significant at the 0.10 level

APPENDIX 3

Regression analysis of mutual fund returns with portfolio holding as at the end of June 1997

SUM: The sum of the frequency ratings of the top 30 stocks held by the funds.
PRODUCT: The weighted average of the frequency rating, using the percentage of assets as the weighting factor.

Panel (A): Growth Fund

	6-Month Nominal Return	6-Month Risk-Adjusted Return	12-Month Nominal Return	12-Month Risk-Adjusted Return
Constant	19.0967 (5.87)***	23.6102 (7.26)**	15.0941 (2.58)**	27.4797 (5.00)***
SUM	-0.0011 (-0.22)	-0.0033 (-0.64)	0.0091 (0.99)	0.0073 (0.84)
PRODUCT	-0.0005 (-0.26)	-0.0003 (-0.12)	0.0037 (0.98)	0.0030 (0.83)
BETA	-7.9783 (-2.57)**	-14.3325 (-4.63)***	4.9000 (0.88)	-11.5591 (-2.21)**
Adjusted R^2	0.0774	0.2574	0.1225	0.0846
F	3.013**	9.321***	4.35***	3.218**
White's General Heteroskedasticity Test	7.00	8.26	13.97	12.72

Panel (B): Growth and Income Fund

	6-Month Nominal Return	6-Month Risk-Adjusted Return	12-Month Nominal Return	12-Month Risk-Adjusted Return
Constant	29.1832 (3.74)***	79.0241 (9.63)***	43.5931 (4.10)***	137.9979 (12.69)***
SUM	-0.0003 (-0.03)	-0.0015 (-0.14)	0.0171 (1.18)	0.0157 (1.06)
PRODUCT	-0.0059 (-0.84)	-0.0068 (-0.92)	0.0096 (1.00)	0.0091 (0.93)
BETA	15.2136 (1.65)	-36.2959 (-3.74)***	27.6736 (2.20)**	-71.2167 (-5.54)***
Adjusted R^2	0.0014	0.2773	0.2475	0.3282
F	1.028	8.546***	7.47***	10.616***
White's General Heteroskedasticity Test	13.52	10.96	9.68	8.69

*** Significant at 0.01 level
** Significant at 0.05 level
* Significant at 0.10 level

APPENDIX 4

Correlation matrix for the four classification variables and beta for 1992/1993 data

SUM: The sum of the frequency ratings of the top 30 stocks held by the funds.

PRODUCT: The weighted average of the frequency rating, using the percentage of assets as the weighting factor.

TILT: The sum of the squared deviations between a fund's weighting in a sector and the sector mean.

INTERVAL: The number of positive deviations from the sector mean minus the number of negative deviations.

	SUM	PRODUCT	TILT	INTERVAL	BETA
SUM	1.0000				
PRODUCT	0.6836	1.0000			
TILT	0.0627	0.1694	1.0000		
INTERVAL	0.0651	-0.1667	-0.7732	1.0000	
BETA	0.0356	0.1037	-0.0756	0.1553	1.0000