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HEDGE FUNDS WITH STYLE

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Abstract: The popular perception is that hedge funds follow a reasonably well defined market-neutral investment style. While this long-short investment strategy may have characterized the first hedge funds, today hedge funds are a reasonably heterogeneous group. They are better defined in terms of their freedom from the constraints imposed by the Investment Company Act of 1940, than they are by the particular style of investment. We study the monthly return history of hedge funds over the period 1989 through to January 2000 and find that there are in fact a number of distinct styles of management. We find that differences in investment style contribute about 20 per cent of the cross sectional variability in hedge fund performance. This result is consistent across the years of our sample and is robust to the way in which we determine investment style. We conclude that appropriate style analysis and style management are crucial to success for investors looking to invest in this market.

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I. Introduction

In the present market environment, no investors are more respected – and feared – than those who manage hedge funds. *TASS*, a major source of data on hedge fund performance, estimates the industry size as of March 1, 2000 at $150 billion. However this number gives but a poor indication of the influence of these funds. Some of the funds are very large; George Soros' funds had a combined capitalization of over $4.6 billion dollars on that date. In addition, funds' influence is leveraged many times over through the use of extensive margin account activity. There is a widespread perception that these managers have the ability to move markets.

As a result, certain hedge fund managers like George Soros have achieved almost popular icon status, celebrated as much for their great wealth and public philanthropy as for their trading prowess. However, there are dissenters. Dr. Mahathir Bin Mohamad, the Prime Minister of Malaysia, in an editorial piece that appeared in the September 23, 1997 issue of the *Wall Street Journal*, said "Whole regions can be bankrupted by just a few people whose only objective is to enrich themselves and their rich clients...We welcome foreign investments. We even welcome speculators. But we don't have to welcome share -- and financial-market manipulators. We need these manipulators as much as travelers in the good old days needed highwaymen."

Despite their public acclaim and despite their profound influence, surprisingly little is understood about hedge funds and what it is they do. The term "hedge fund" seems to imply market neutral, low risk trading strategies, whereas the extensive use of leverage in these funds appears to suggest a high level of risk. In fact, associating the term "hedge" with the name George Soros suggests in the popular mind that this term can be associated with any kind of high risk trading strategy.

The term “hedge fund” was actually coined by Carol Loomis in a 1966 *Fortune* magazine article to describe the investment philosophy of one Alfred Winslow Jones. His fund had two general characteristics. It was “market neutral” to the extent that long positions in securities he determined were undervalued were funded in part by taking short positions in overvalued securities. This was the “hedge”, and the net effect was to leverage the investment so as to make very large bets with limited investment resources. His second innovation was the introduction of a substantial incentive fee initially set at 20% of realized profit without any fixed management fee.

Today, the term “hedge fund” encompasses investment philosophies that range far from the original “market neutral” strategy of Jones to include the global macro styles of people like Soros and Julian Robertson. In addition, many investment firms are simply renaming their trading desks as “hedge funds” and many traditional equity managers are rushing to get into what appears to be a very lucrative business. As a practical matter, hedge funds are best defined by their freedom from regulatory controls stipulated by the Investment Company Act of 1940. These controls limit fund leverage, short selling, holding shares of other investment companies, and holding more than 10% of the shares of any single company. Compensation terms typically include a minimum investment, an annual fee of 1% - 2%, and an incentive fee of 5% to 25% of annual profits. The incentive fee is usually benchmarked at 0% return each year, or against an index such as the U.S. or U.K. treasury rate. This compensation structure usually includes a “high water mark” provision that adds past unmet thresholds to current ones.

Hedge funds are typically set up as limited partnerships or limited liability companies providing specialized investment vehicles for high net worth individuals and institutions. The National Securities Markets Improvement Act of 1996 limits participation to at most 500 “qualified investors", individuals who have at least $5 Million to invest and institutions with capital of at least $25 Million. Exemption from regulatory oversight and investment restrictions faced by other investment companies comes at the cost of restrictions on public advertising and solicitation of investors. Absence of regulatory oversight means that reliable information on hedge funds is hard to come by. In addition the same regulations imply that the funds cannot disseminate information about their activities even if it were in their interest to do so. This may be one reason so little is known about this sector of the financial market.

Despite the relative lack of information about hedge funds, institutional investors have taken an increasingly active interest in hedge funds as an asset class. What evidence we have about the historical risk and return characteristics of hedge funds suggests they may be attractive as a portfolio asset. Yet, as we show in this paper, hedge funds are anything but a monolithic asset class in the traditional sense of the word. The hedge fund universe encompasses a range of different strategies and approaches and specialities. Some managers add value through knowledge of special asset markets, others through trading skills, and others through superior asset pricing models. It is this very variety that poses both a challenge and an opportunity. The challenge is comprehending and bench marking managers whose operations are essentially opaque, whose instruments vary widely, and who in many cases eschew predictable passive factor exposures. The opportunity lies in the diversification that the varieties of hedge funds present. A substantial sub-industry of fund-of-funds has emerged to allow investors to hold a diversified portfolio of shares in hedge fund vehicles, spreading their exposure to the class across a range of strategies.

The purpose of this paper is to shed some light on the stylistic differences across hedge funds. We ask a few simple questions. First, in light of the extraordinary variety of hedge fund strategies, are there a few basic styles that they pursue? Second, are these styles meaningful to investors – that is, do they explain differences in performance? Third, are there any significant trends in these styles that investors and analysts should know about?

To address these questions, we study the monthly return history of a large database of hedge funds over the period 1989 through to January 2000 and find that there are in fact a number of distinct styles of management. We use a systematic, quantitative approach to using both the return history and the self-reported style information to understand and characterize the major categories of hedge fund styles during the sample period. We find that differences in investment style contribute about 20 per cent of the cross sectional variability in hedge fund performance. This result is consistent across the years of our sample and is robust to the way in which we determine investment style. Furthermore, differences in style account for significant differences in risk taking by fund managers. We conclude that appropriate style analysis and style management are crucial to success for investors looking to invest in this market.

This paper is structured as follows. The next Section describes the data and methodology of our work. Section three reports the results of our empirical analysis, and Section four concludes.

II. Data and Methodology

II.1 Data

TASS is a New York-based advisory and information service that maintains a large database of hedge fund managers that we used in this analysis. The fund return data provided by TASS is used in recent research by Fung and Hsieh (1997). A competitor to TASS, Managed Account Reports (MAR) has data on the hedge fund population as well, and this is the data used by

Ackerman, McEnally and Ravenscraft (1999)[1]. Neither of these two sources is a “follow-forward” database of the kind used in Brown Goetzmann and Ibbotson (1999). Consequently we could not verify the extent to which defunct funds have been dropped from the sample until very recently. TASS has recognized the importance of maintaining defunct funds in their data, and since 1994 they have kept records of hedge funds that cease to operate. Because of the limited coverage of the database before 1988, we use TASS data for the period 1989-1999 in our study.

In addition to rate of return data, TASS also provides extensive descriptive material each one of the hedge funds they cover as of January 2000. Based on available information from survey responses and fund disclosure documents they attempt to define the principal focus of the hedge fund in an effort to classify hedge funds into one of 17 different types. The TASS hedge fund classifications are presented in Table 1. While the TASS database covers a range of investment categories it is evidently under-represents several important classifications, most notably the fund-of-funds category. There are several important caveats to this classification. These categories are not very precise nor are the terms used well defined[2]. To the extent that they are based on manager survey responses they are also subject to strategic self-misclassification. In Brown and Goetzmann (1997) we study the way in which mutual funds report themselves to Weisenberger, which publishes an annual survey of mutual funds. In virtually every case, changes in self-classification had the net effect of increasing returns relative to the new defined benchmark. Given that such strategic behavior

[1]Ackerman, McEnally and Ravenscraft (1999) also includes data from another vendor, Hedge Fund Research.

[2]Many hedge funds report multiple specializations. For example most international focus hedge funds are invested in both equity and fixed income securities (72% by value of Asian equity hedge funds also report a fixed income focus as of January 2000). The numbers in Table 1 are the principal focus investment interest as determined by TASS.

can occur in the heavily regulated mutual fund environment, we should expect it to be a more severe problem in the far less regulated world of hedge funds.

II.2 Generalized Style Classification [GSC] methodology

II.2.1 Estimation

There is a long tradition of characterizing investment funds according to parameters estimated via a linear model of returns. The technology of asset pricing was first applied by Jensen (1968) to grouping mutual funds according to their systematic risk characteristics. Conner and Korajczyk (1986), Lehmann and Modest (1987), Grinblatt and Titman (1989) and Elton, Gruber, Das and Hlavka (1993) all apply linear asset pricing methods to differentiate mutual funds on the basis of systematic risk characteristics. Sharpe(1992) observed that since mutual fund returns are highly correlated with broad asset class returns, this linear model can be used to characterize the portfolio policies of mutual fund managers and provide a reliable basis for determining investment style. As a result, the model is widely used in practice to manage exposure to investment management style.

However, this simple linear model does not appear to work very well for hedge funds. Fung and Hsieh (1997) report that while mutual fund returns have high and positive correlation with asset class returns, hedge fund returns have low and sometimes negative correlation with the same asset class returns. They attribute this failure to the dynamic use of leverage and changes in asset exposure by hedge funds. This kind of active portfolio management affects performance measurement in non-trivial ways. Dybvig and Ross (1985), for instance, show how linear risk models fail to properly rank fund managers when they change their asset weights through time. Fung and Hsieh (1997) observe that this attribute also causes problems for a style based interpretation of the asset class loadings. The way in which fund managers change asset weights in response to economic circumstances can itself be legitimately characterized as part of their asset management style.

In Brown and Goetzmann (1997) we suggest a simple but quite general procedure to identify asset management styles where asset weights vary through time. The objective of this procedure is to use past returns to determine a natural grouping of funds that has some predictive power in explaining the future cross-sectional dispersion in fund returns. Such groupings are referred to as *styles*. If there are K such styles the *ex post* total return in period *t* for any fund can be represented as:

$$R_{jt} = \alpha_{Jt} + \beta_t' I_t + e_{jt} \qquad \textbf{(1)}$$

where fund *j* belongs to style *J*. There are several ways of interpreting this equation. In a traditional financial economics framework, this equation refers to a multifactor or a multibeta model. The factor loadings on factors I_t are given by β_{Jt}. These loadings are allowed to change through time. As Sharpe (1992) points out, if we regard the factors I_t as returns on index portfolios, the factor loadings can be thought of as equivalent portfolio weights associated with a dynamic portfolio strategy that might be associated with the style in question. In an interpretation closer to that of financial practitioners β_{Jt} refers to a characteristic of a typical stock in the *Jth* style classification (size, market to book, price earnings multiple, etc.) and I_t is the return to that attribute (c.f. Lakonishok, Shleifer and Vishny, 1994).

Regardless of how we interpret the equation, the style classifications will explain the cross-sectional dispersion of fund returns. Writing the equation as :

$$R_{jt} = \mu_{Jt} + \varepsilon_{jt} \qquad \textbf{(2)}$$

where μ_{Jt} is the expected return for style J conditional upon the factor realization I_t. If the idiosyncratic return component ε_{jt} has zero mean *ex ante* and is uncorrelated across securities, the classification into styles will suffice to explain the cross-sectional dispersion of fund returns to the extent that μ_{Jt} differs across styles. It is important to note that Equation (2) justifies the common industry practice of using style benchmarks to evaluate performance of money managers within a given style[3]

The task of assigning funds to style categories can be thought of as a problem in endogenously defining regimes (see for instance Quandt 1959 and 1960). In this way, it bears a "family" resemblance to switching regression, although, unlike the switching regression, an exact solution to the stylistic classification problem is only obtained through exhaustive combinatorics. The approach we use finds a local optimum via the minimization of a "within-group" sum of squares criterion, over a specific time period, t=1...T. The inputs to the procedure is a T by N matrix of monthly returns for a set of N mutual funds. We group the N funds together into K styles by minimizing the within-style mean returns for each period t=1..T. Thus, we are jointly estimating the time-series of mean returns for the styles J=1..K (μ_{Jt}) for t=1..T, and the membership to each style. The benefit of the resulting classification is that groups could result from either fixed portfolio strategies, such as similar asset compositions, or from dynamic portfolio strategies, such as portfolio

[3]To see this, note that the style benchmark $\hat{\mu}_{Jt}$ given as the value-weighted average return within each style category, $\hat{\mu}_{Jt} = \sum_{j \in J} w_{jt} R_{jt}$, is an unbiased estimator of the true expected return conditional on the factor realizations as of date t: $E(\hat{\mu}_{Jt} - \mu_{Jt}) = E\left(\sum_{j \in J} w_{jt} \varepsilon_{jt}\right) = 0$.

insurance rebalancing.

The classification procedure assumes that we know the number of styles. Conditional upon restrictions upon the exact number of groups, Equation (2) is perfectly well-specified and can be used to estimate the style groupings. Equation (1) gives further insight into the nature of time-varying portfolio strategies, however, the parameters in this equation are not identified without further restrictions[4]. In order to implement our style classification [SC] algorithm, we pre-specify the number of styles.

A modification of the basic algorithm is a *generalized* least squares procedure [GSC] which allows time-varying and fund-specific residual return variance. By scaling observations by the inverse of the estimated standard deviation, we decrease the influence of extreme observations in the classification process. In addition, GSC corrects for differences among managers that occur solely because of differences in scale or degree of diversification. The details of the GSC algorithm are fully described in Brown and Goetzmann (1997).

It is important to note that the SC and GSC procedures makes minimal demands on the available data. We can estimate Equation (2) *without needing to know* factor loadings or style attributes represented by the vector β_{Jt} which may well change from period to period. We only need to know *ex post* returns on individual funds.

II.2.2 Identification

One of the difficulties with estimating styles strictly from returns is that it is difficult to map the returns-based styles back to the self reported styles. Fund and Hsieh (1997), for example, get

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[4]A restriction sufficient for identification purposes is to assume that the portfolio strategy is constant over a number of months greater than the number of factors.

some sense of what styles managers use by looking at the reported activities of the funds that exhibit similar loadings on dynamic factors extracted from the hedge fund universe. Brown and Goetzmann (1997) cross-tabulate membership in a returns-based style with membership in a self-reported style, and then normalize each GSC style to understand differences in style composition. We follow the same procedure in this paper. Scaled cross-tabulation allows us to represent each style in terms of a mixture across the range of self-represented manager activities. This in turn, helps us label the estimated styles according to the preponderance of managers in each group.

III Results

III.1 GSC Style Classifications

It is interesting to note that the self-classifications, sometimes ambiguous and difficult to interpret, are indeed reasonably descriptive of hedge fund styles. The TASS classifications that we have applied are dated January 1, 2000. There is no guarantee that these hedge fund characteristics are constant over the period of our sample. Indeed, as we mentioned before, there is every reason to believe that these self-reported classifications vary as managers define themselves relative to favorable benchmarks. Yet, when we determine GSC classifications for the three year period up to December 1999, there is a remarkable agreement between these return-based classifications and the classifications that TASS has determined on the basis of fund disclosures and questionnaires. Figure 1 gives the scaled cross-tabulation breakdown of each GSC style relative to the estimated assets under management in each TASS category as of January 1, 2000. Whether we consider eight styles or five styles, there are some clearly defined categories. In the case of eight styles, we find that GSC3 is a property investment style, GSC3 is a US equity focus, GSC7 is emerging markets, and GSC1 and GSC8 are aggressive international styles, the first as a directional equity style and the second as a global macro style. GSC 4 and GSC 5 both have a significant representation of non-directional/relative value funds. This is the "classical" hedge fund style. We find that it spreads primarily between two of our returns-based categories. "Event-driven" managers spread across four of our GSC styles – GSC 1 is largely foreign investment and GSC 5 is largely domestic. Thus, presumably GSC 5 captures the U.S. focused M&A arbitrage funds in the sample.

With five styles the results are similar, although certain of the categories appear to have merged. This suggests that five stylistic classifications may not be sufficient to describe the breadth of investment management philosophies adopted by hedge fund managers[5]

III.2 Comparative Performance

How well does the returns-based procedure perform relative to stated investment objectives? The answer will clearly depend on the use to which we intend to put the resulting style classifications. The ability to interpret the styles is clearly important. However, if the style classifications are ambiguous or if they bear no relationship to returns, then they have limited utility in an investment management context. In Brown and Goetzmann (1997) suggest that an appropriate criterion for evaluating style classifications is the extent to which these classifications can explain cross sectional differences in future year returns.

To implement this, we classify funds into styles using three years of data, and then regress the cross section of fourth year fund returns against these classifications. We repeat this exercise for

[5]Fung and Hsieh (1997) find at least five stylistic categories using their returns-based procedure for identifying styles. A Chi-square test (Brown and Goetzmann 1997) indicates that there are at least eight distinct styles. This result is consistent with what we observe in Figure 1.

each three year period of the data, reporting the adjusted R^2 generated by regressing subsequent period returns against a matrix of dummy variables that indicate whether each fund belongs to a particular style. If the style classification contains information about future differences in returns, we would expect these regressions to explain a significant amount of cross-sectional variance. This same procedure is performed for the industry classifications. A comparison of adjusted R^2 indicates which has the superior predictive ability[6].

The results of this procedure are presented in Table 2. Style differences account for approximately 20 percent of the cross-sectional dispersion in hedge fund returns. On average, the returns-based procedure with eight style classifications explains a greater percentage of the variability of subsequent returns than does the 17 category TASS classification. This is true whether we consider R^2 or adjusted R^2.[7] However, this was true only for the 8 style GSC analysis. Assuming only 5 styles, the 17 TASS classifications did somewhat better than the returns-based procedure. This is further evidence that 5 styles may not be sufficient to explain the heterogeneity of hedge fund investment philosophies.

III.3 Predicting Fund Performance with Style

An important activity of fund-of-funds is forecasting which managers will out-perform their peers. In this section we show that it is essential to establish the correct peer group before looking at performance persistence. Figures 2 through 7 provide a graphical representation of the extent to

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[6]This test is actually biased against the returns-based procedure, as the industry classifications are determined as of January 1, 2000, a date subsequent to all of our data.

[7]The average unadjusted R^2 was 24.15% for the 8 factor GSC classification, and 22.68% for the 17 classifications published by TASS.

which style membership explains returns. Each scatter plot gives the fund returns in each year as a function of the annual fund return in the previous period. Each point is colored according to the style membership of the fund determined on the basis of the prior three years of data. It is important to note that the second year return data depicted on the y axis was not used for the determination of fund style. The vertical line gives the median hedge fund return for the first year in each two year comparison, while the horizontal line gives the median fund return for the second year (y axis). If there were persistence in hedge fund returns, there would be a preponderance of funds in the upper right quadrant (Winner-Winner). The red line gives the regression of fund returns in the second year against annual returns in the first year. Again, with persistence of fund returns the slope of this line should be significantly positive.

Consistent with findings in our earlier study of off-shore hedge funds (Brown, Goetzmann and Ibbotson 1999) we find very little evidence of persistence in annual hedge fund returns[8]. With the exception of comparison years 1995-96 and 1996-97 the winner-winner quadrant is noticeably sparse and the slope of the regression line is negative or insignificantly positive. While the data may suggest limited evidence of persistence for the period 1995-97, one has to be very careful interpreting the results. Note that the preponderance of the funds appearing in the top right Winner-Winner quadrant are marked with crosses. These crosses signify that the fund in question did not survive in the dataset the following year. Ackerman, McEnally and Ravenscraft (1999) suggest that the funds that leave the database are often successful managers that see no need to continue reporting to the hedge fund data service. Brown Goetzmann and Park (2001) and others show on the contrary that

[8]Agarwal and Naik (2000) also find that there is little evidence of persistence in annual returns. However, they indicate that there is indeed evidence of persistence of quarterly and to a lesser extent semi-annual returns.

these fund managers are the ones that took considerable risk and lost substantially immediately prior to leaving the database.

Inspecting the figures more carefully we see immediately the reason for the apparent persistence and reversals. Following Agarwal and Naik (2000), we consider the influence style has in determining the persistence of hedge fund performance. Each of the style categories tend to cluster together in terms of their returns. Since the styles were determined on the basis of returns prior to the second comparison year, this result cannot be an artefact of the way styles were determined. Some years certain styles do well. In other years they do not do so well. The fact that in any given year a particular style or hedge fund strategy does well is by itself evidence that the strategy will earn high returns in future years. Thus, our evidence is bad news for analysts hoping to use historical data to forecast future winners, but very good news for fund-of-fund investors. We find that diversification across GSC styles is an effective way to reduce exposure to holding a losing set of managers in any given year.

III.4 Value-at-Risk and Styles

Many analysts see styles as a surrogate for risk exposure. Is there any evidence which suggests that hedge fund styles separate managers out in terms of the risk they are willing to bear? We examined the value-at-risk of all of the hedge fund managers in the TASS universe. The median value-at-risk for each of eight GSC styles was calculated for the period 1993 through 1999, and plotted in Figure 8. To guarantee that the value-at-risk was determined independently of the returns-based style, the month in which value-at-risk is determined was excluded from the data used to allocate funds to styles. We see that the styles of management group together into three distinct risk classes. The global equity hedge, US equity hedge and global macro styles (GSC1, GSC2 and GSC8) cluster together. Managers in these style categories typically take more risk than other managers. Note particularly the spike in value at risk in September 1998 coincident with the problems at Long Term Capital Management (which is not part of our database). This sudden increase in value-at-risk also was evident in the relative value styles GSC4 and GSC5, and GSC6 which like GSC1 has a significant fraction of funds identifying themselves as non-US equity fund managers.

What might explain this jump in the VAR for this group. It is tempting to interpret this as evidence of either increasing asset market volatility or alternately increasing leverage of the funds in the sample. The increase in volatility is consistent with the increase in the volatility of U.S. equity indices over this period, as well as an increase in the idiosyncratic component of U.S. equity risk. On the other hand, the fund volatility level is a variable set jointly by the manager and creditors. It is somewhat surprising that in the wake of the LTCM collapse, creditors have been willing to tolerate an increase in hedge fund volatility. One could infer that leverage has increased, despite credit constraints, because arbitrage opportunities have become relatively scarce.

III.3 Comparison with other returns-based style procedures

The GSC approach we describe in this paper is certainly not the only returns-based style procedure. It is useful to compare how our methodology performs when benchmarked against alternatives. In the mutual fund area, the constrained linear regression approach of Sharpe (1992) is very commonly applied. The Sharpe procedure is typically applied with passive benchmarks – that is, standard asset classes are used as the regressors in an equation in which the dependent variable is the fund of interest and the independent variables are passive asset class returns. The estimated coefficients are the interpretable as portfolio weights.

In fact, this approach corresponds to estimating Equation (1) where the factors I_t are proxied by asset class returns and the factor loadings β_t are assumed constant over the estimation period and are interpreted as the average portfolio weight invested in each of the reference assets over this period. Fung and Hsieh (1997) argue persuasively that the Sharpe (1992) approach ignores the dynamic component of asset management style that is characteristic of hedge fund management. In an attempt to capture dynamic styles that are useful for asset allocation decisions and bench marking, Fung and Hsieh (1997) form K reference assets that maximally correlated with the first K principal components, using a portfolio of hedge funds for each reference assets that has a high "loading" on the principal component. In this context, while is is not an explicit procedure for fund classification, membership in the "style" is determined by whether a fund loads mostly on one of reference assets. In like manner, once could classify funds by their loadings on one of the pre-specified styles.

In Table 3 we report results from cross sectional regressions in which we explain differences in three-year performance according to the GSC classification, the classification based on the Fung and Hsieh (1997) approach, and classification based on the Sharpe (1992) approach. In particular, we estimate the first five principal components using hedge fund returns for which we have three years of continuous data and define a set of reference assets maximally correlated with these principal components. We then apply the Sharpe (1992) procedure to these reference assets. The returns-based style is then given as the reference asset on which the fund has the highest possible loading. In the same way, we use pre-specified asset classes as reference assets and then classify according to which factor the fund loads most highly upon.

In Table 3, we find that principal components-based styles explain only about eight percent of the cross sectional variability of post-sample returns. This result follows whether we base the style analysis on five principal components (as in Fung and Hsieh (1997) or eight principal components. The use of pre-specified factors, rather than principal component-based reference assets is an improvement. Classifications based on loadings on eight standard predetermined performance benchmarks[9], which actually explain 11.75 percent of the cross-sectional variation in returns. Both are apparently less powerful than the GSC methodology.

The horse race in Table 3 is not entirely fair, however. Neither the Fung and Hsieh (1997) or the Sharpe (1992) procedures were intentionally designed to classify funds, rather they were designed to explain fund performance relative to appropriate benchmarks. For this reason it is not difficult to understand why it is that the principal components procedure performs so poorly. The problem does not relate to the use of hedge fund return benchmarks. After all, the GSC approach also uses such benchmarks. The problem relates to principal components and the difficulty of estimating them. In an asset return context, all securities tend to load positively on the first principal component which then by construction is highly correlated with an equally weighted average of the component securities, while the remaining components capture elements of returns uncorrelated with the first (Brown, 1989). As a consequence the first component is estimated with precision and second and remaining components are estimated with considerably less precision. This suggests that while principal components may provide an excellent set of benchmarks for hedge fund performance they may be less successful in a returns-based style management context. We investigate this possibility in Table 4.

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[9]These predetermined benchmarks include Fama-French Large Growth, Large Value, Small Growth and Small Value index returns, as well as Ibbotson Long Term Government and 30 day returns and MSCI Europe and Asia/Pacific total return indices.

In Table 4 we consider the correlation of post-sample returns with loadings on alternative hedge fund benchmarks – GSC, Principal Components and Pre-Specified Factors. We now find that the performance of the principal components-based benchmarks is extremely close to the performance of the GSC based benchmarks in the five styles case, and only a little worse than the GSC approach in the eight styles case. In addition, consistent with the findings of Fung and Hsieh, we also find that the predetermined factor loadings explain less of the cross-sectional variability in returns than do any of the returns-based benchmark loadings. However, the most interesting finding from Table 4 is the fact that the principal components based procedure (with eight factors) now performs almost as well as the TASS 17 descriptors in explaining the cross section dispersion of annual returns. Whether we determine styles on the basis of careful returns-based analysis, or simply rely on self-reported characterizations of investment style, the result is the same. Differences in investment style contribute about 20 per cent of the cross sectional variability in hedge fund performance.

The implications of Table 3 and Table 4 together is that, when analysts need to estimate factor exposures and report continuous variables about hedge funds such as how they might load on a dynamic strategy, then the "beta" models do a fair job. When identification or classification is needed, then the GSC algorithm is a very useful tool. It not only differentiates funds in a way that spreads future performance, but it also provides reasonable factors which can be used in the context of factor exposure estimation. Finally, with the scaled cross-tabs, the identity of the groups can be generally ascertained.

IV Conclusion

Despite the public interest in hedge funds and their important role in the financial markets, surprisingly little is known about their similarities and differences. In part, this is because they are not obliged to make public reports of their asset holdings or performance, but also in part it is because they perceive it is in their business interest to appear enigmatic players in the global capital markets. As a result there is much confusion about who they are and what they do.

The popular perception is that there is a well defined market-neutral hedge fund style of investing. By a close analysis of the returns history over the last ten years we have discovered that this perception is false. There are at least eight distinct styles or philosophies of asset management currently employed by hedge funds, and risk exposure depends very much on style affiliation. Furthermore, we find that the persistence (or reversal) of fund returns from year to year has a lot to do with the particular style of fund management. In fact, 20 percent of the cross sectional variability of fund returns can be explained solely by the style of management. This result is robust to the way in which we choose to define styles, and is similar for most of the years of our sample.

One interesting finding is that self-reported characterizations of asset management style do almost as well as some of the latest return-based procedures. However, this result should be treated with some considerable care. The fact that hedge funds are for the most part unregulated entities and the fact that there are no generally accepted standards for hedge fund style classification means that there are almost unlimited opportunities for individual funds to engage in strategic self-misclassification. Given the absolute importance of style affiliation in determining risk exposure and return outcome, we conclude that appropriate style analysis and style management are crucial to success for investors looking to invest in this market.

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Table 1: TASS provided hedge fund classifications as of January 1, 2000

Principal Focus	Number of Funds	Percent of total	Estimated Assets under Management ($Million)	Percent of total
US Equity Hedge	229	17.71%	25,137	16.62%
European Equity Hedge	68	5.25%	11,453	7.57%
Asian Equity Hedge	22	1.66%	6,867	4.54%
Global Equity Hedge	55	4.24%	18,390	12.16%
Dedicated Short Seller	11	0.85%	545	0.36%
Fixed Income Directional	25	1.93%	977	0.65%
Convertible Fund (Long Only)	11	0.85%	688	0.46%
Event Driven	128	9.88%	17,505	11.57%
Non Directional/Relative Value	147	11.34%	21,512	14.22%
Global Macro	24	1.85%	10,666	7.05%
Global Opportunity	3	0.23%	31	0.02%
Natural Resources	4	0.31%	17	0.01%
Pure Leveraged Currency	233	17.94%	18,186	12.02%
Pure Managed Future	36	2.82%	1,562	1.03%
Pure Emerging Market	174	13.43%	6,528	4.32%
Pure Property	125	9.65%	11,168	7.38%
Fund of Funds	1	0.08%	32	0.02%
Total	1296	100.00%	151,265	100.00%

Notes: In the case of 56 funds (total estimated assets of $2.1Billion) TASS identified two principal foci. For the purpose of this table such funds were assumed to have been split evenly between each investment focus.

Table 2: Cross-sectional variance explained by different classification procedures

Year	N	Regressing returns on classifications: Adjusted R^2 GSC 8 classifications	GSC 5 classifications	TASS 17 classifications
1992	149	0.3827	0.1713	0.4441
1993	212	0.2224	0.1320	0.1186
1994	288	0.1662	0.1040	0.0986
1995	405	0.0576	0.0548	0.0446
1996	524	0.1554	0.0769	0.1523
1997	616	0.3066	0.1886	0.2538
1998	668	0.2813	0.2019	0.1998
	Average	0.2246	0.1328	0.1874

This table compares the adjusted R^2 regressing annual fund returns against several alternative fund classifications. The GSC procedure uses a 36 month estimation period prior to and including December of the year given in the left hand column. GSC classifications were determined both for an 8 style classification as well as a 5 style classification. The third classification considered is the 17 fund descriptors given in the TASS database for funds in the sample as of January 2000. The out of sample test period corresponds to the annual return period subsequent to the year given in the left hand column. The cross section of test period returns on funds are regressed against (K - 1) dummy variables, where $\delta_{ki} = 1$ for fund I in category k, zero otherwise.

Table 3: Cross-sectional variance explained by different classification procedures

Year	N	Regressing returns on classifications: Adjusted R^2				
		Style Identified by GSC Procedure		Style identified by Principal Components		Predetermined benchmarks
		8 classifications	5 classifications	8 classifications	5 classifications	8 classifications
1992	198	0.3622	0.1859	0.0572	0.0782	0.1769
1993	276	0.1779	0.0965	0.0351	0.0322	0.1748
1994	348	0.1590	0.1002	0.0761	0.0665	0.0481
1995	455	0.0611	0.0601	0.0799	0.0803	0.0862
1996	557	0.1543	0.0781	0.0286	0.0238	0.0691
1997	649	0.2969	0.1810	0.0211	0.0471	0.0642
1998	687	0.2824	0.2033	0.2862	0.2863	0.2030
Average		0.2134	0.1293	0.0835	0.0878	0.1175

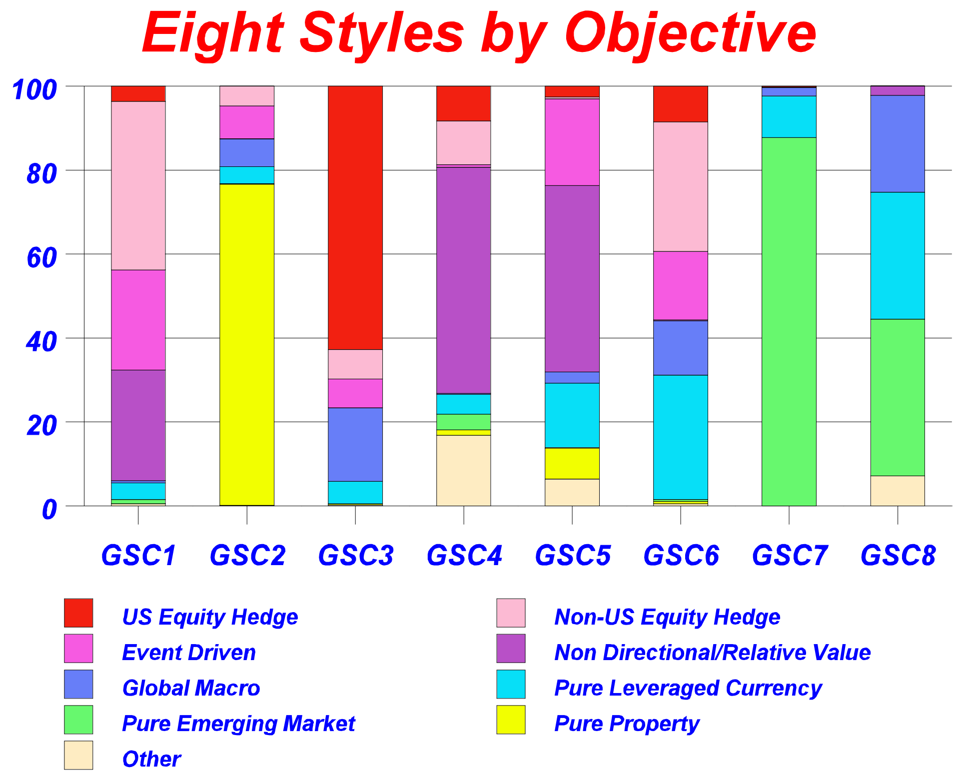
This table compares the adjusted R^2 regressing annual fund returns against several alternative returns-based fund classifications. Each procedure uses a 36 month estimation period prior to and including December of the year given in the left hand column. The GSC procedure is described in Brown and Goetzmann (1997) while the Principal Components procedure is described in Fung and Hsieh (1997). In the latter procedure the loadings on K factors are estimated by regressing individual fund returns on portfolios maximally correlated with the first K principal components of fund returns, with coefficients constrained to be positive and to sum to one (Sharpe (1992)) The fund classification was determined by the benchmark on which the fund loaded most heavily. Each returns-based procedure was applied assuming both 8 and 5 styles. The predetermined benchmark refers to a classification based on standard performance benchmarks, Fama-French Large Growth, Large Value, Small Growth and Small Value, as well as Ibbotson Long Term Government and 30 day returns and MSCI Europe and Asia/Pacific total return indices. The out of sample test period corresponds to the annual return period subsequent to the year given in the left hand column. The cross section of test period returns on funds are regressed against (K - 1) dummy variables, where $\delta_{ki} = 1$ for fund I in category k, zero otherwise.

Table 4: Cross-sectional variance explained by different factor loadings

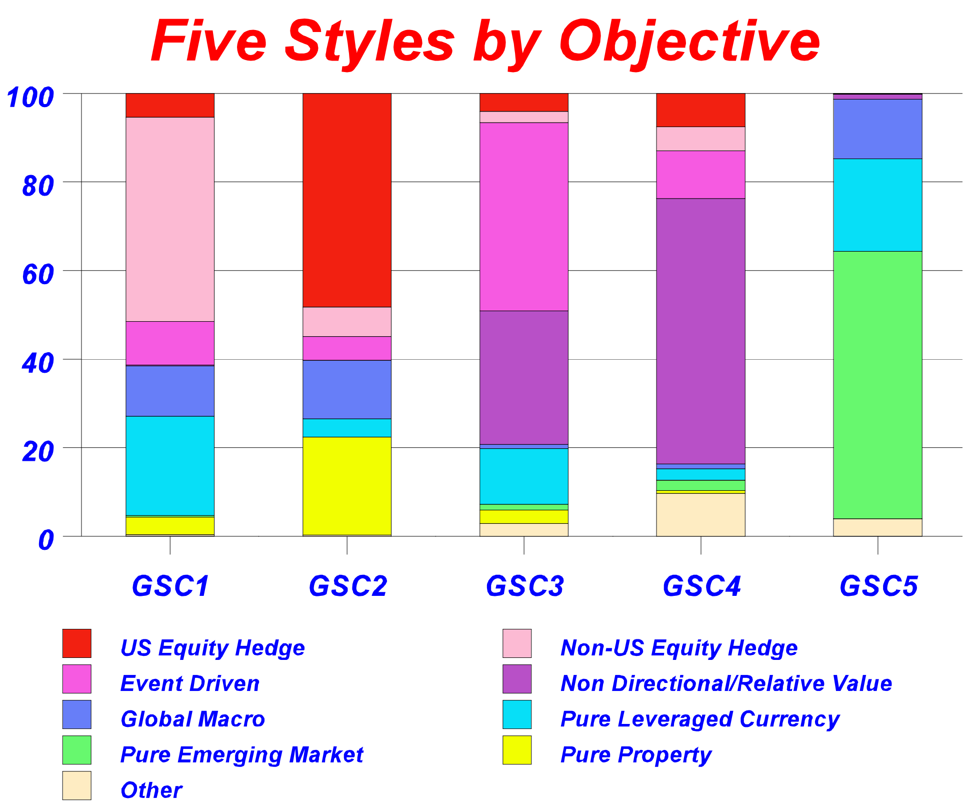
		Regressing returns on factor loadings: Adjusted R^2				
		Loadings on GSC factors		Loadings on Factors from Principal Components		Predetermined benchmarks
Year	N	8 classifications	5 classifications	8 classifications	5 classifications	8 classifications
1992	198	0.2742	0.2186	0.1607	0.1503	0.2552
1993	276	0.2170	0.1437	0.0928	0.0945	0.0932
1994	348	0.1760	0.1327	0.1577	0.1592	0.0700
1995	455	0.0670	0.0595	0.0783	0.0711	0.0829
1996	557	0.1444	0.0817	0.0888	0.0709	0.0349
1997	649	0.3135	0.2584	0.3069	0.2506	0.0899
1998	687	0.2752	0.2381	0.3744	0.3281	0.3765
Average		0.2096	0.1618	0.1799	0.1607	0.1432

This table compares the adjusted R^2 regressing annual fund returns against several alternative returns-based factor loadings. These loadings were determined on the basis of a prior 36 month estimation period up to and including December of the year given in the left hand column. The GSC loadings were obtained by regressing fund returns on GSC benchmarks (see Brown and Goetzmann (1997)) constraining the coefficients to be positive and to sum to one (Sharpe (1992)). The principal components benchmarks were obtained by a similar regression procedure using principal component-based benchmarks. This benchmark procedure is described in Fung and Hsieh (1997). The predetermined benchmark refers to a classification based on standard performance benchmarks, Fama-French Large Growth, Large Value, Small Growth and Small Value, as well as Ibbotson Long Term Government and 30 day returns and MSCI Europe and Asia/Pacific total return indices. The out of sample test period corresponds to the annual return period subsequent to the year given in the left hand column

Figure 1

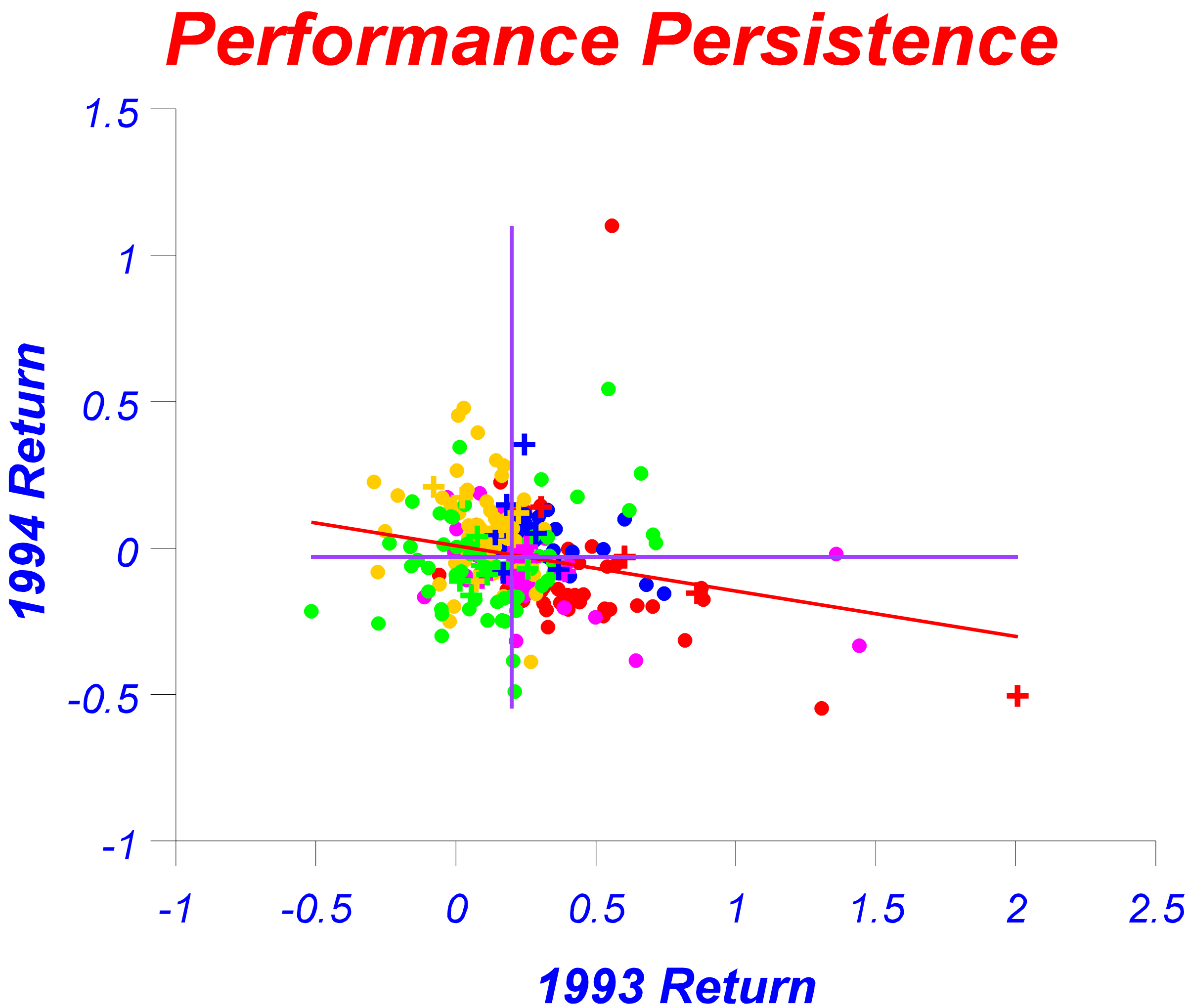


Eight Styles by Objective
100
80
60
40
20
0
GSC1
GSC2
GSC3
GSC4
GSC5
GSC6
GSC7
GSC8
US Equity Hedge
Non-US Equity Hedge
Event Driven
Non Directional/Relative Value
Global Macro
Pure Leveraged Currency
Pure Emerging Market
Pure Property
Other



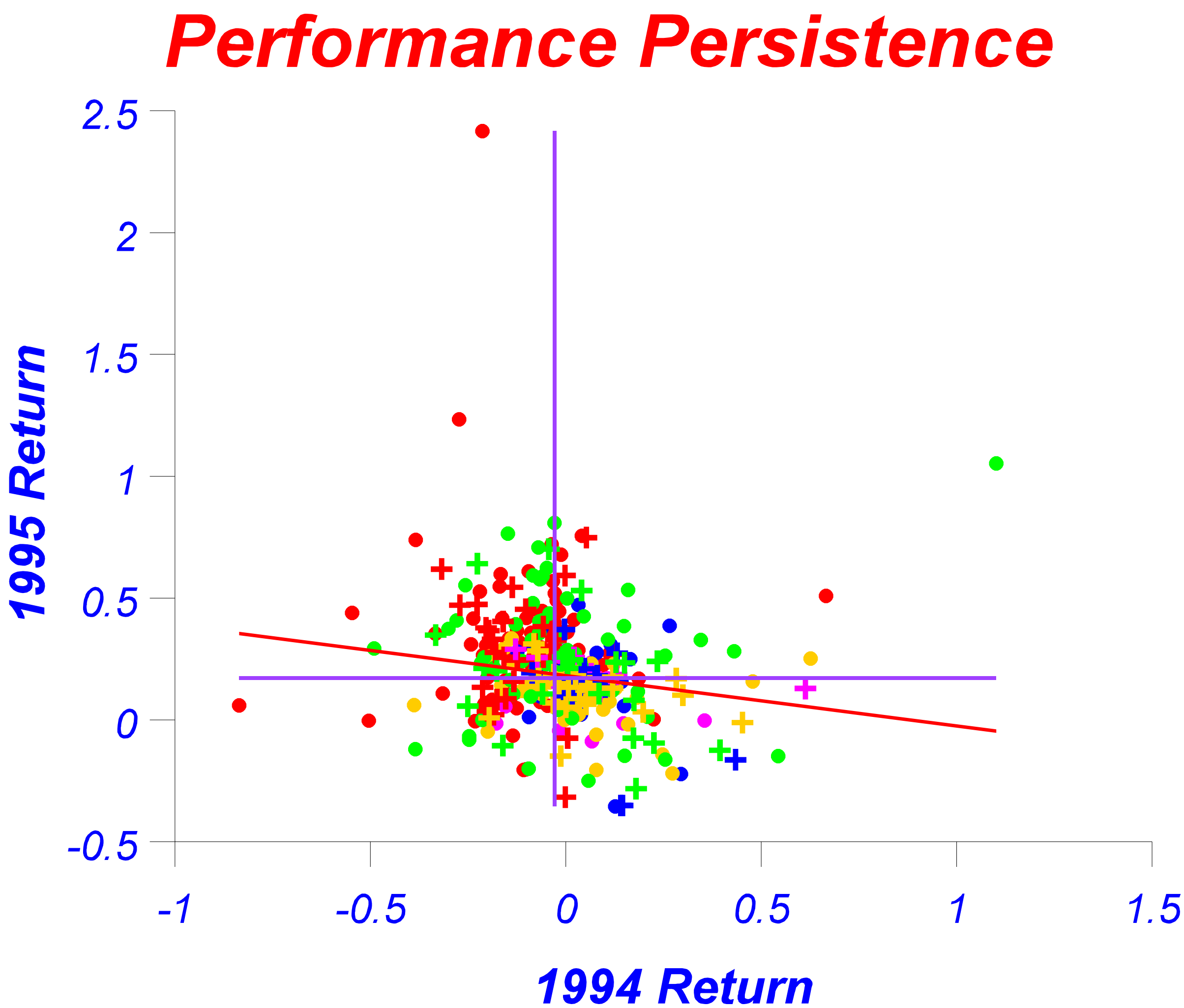
Five Styles by Objective
100
80
60
40
20
0
GSC1
GSC2
GSC3
GSC4
GSC5
US Equity Hedge
Non-US Equity Hedge
Event Driven
Non Directional/Relative Value
Global Macro
Pure Leveraged Currency
Pure Emerging Market
Pure Property
Other

Figure 2



Performance Persistence
1.5
1
0.5
0
-0.5
-1
1994 Return
-1
-0.5
0
0.5
1
1.5
2
2.5
1993 Return

Figure 3



Performance Persistence
2.5
2
1.5
1
0.5
0
-0.5
1995 Return
-1
-0.5
0
0.5
1
1.5
1994 Return

Figure 4

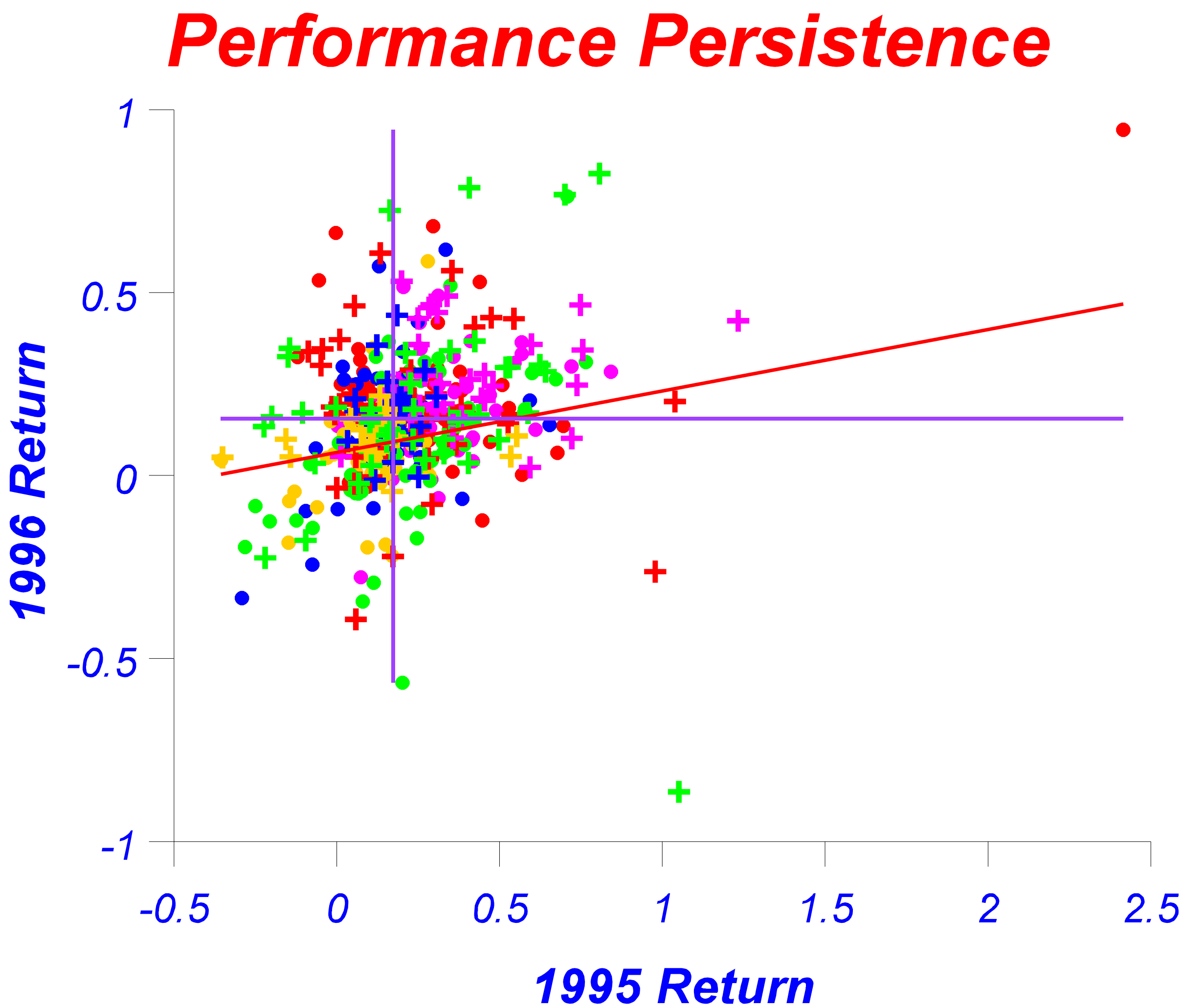

Performance Persistence
1
0.5
0
-0.5
-1
1996 Return
-0.5
0
0.5
1
1.5
2
2.5
1995 Return

Figure 5

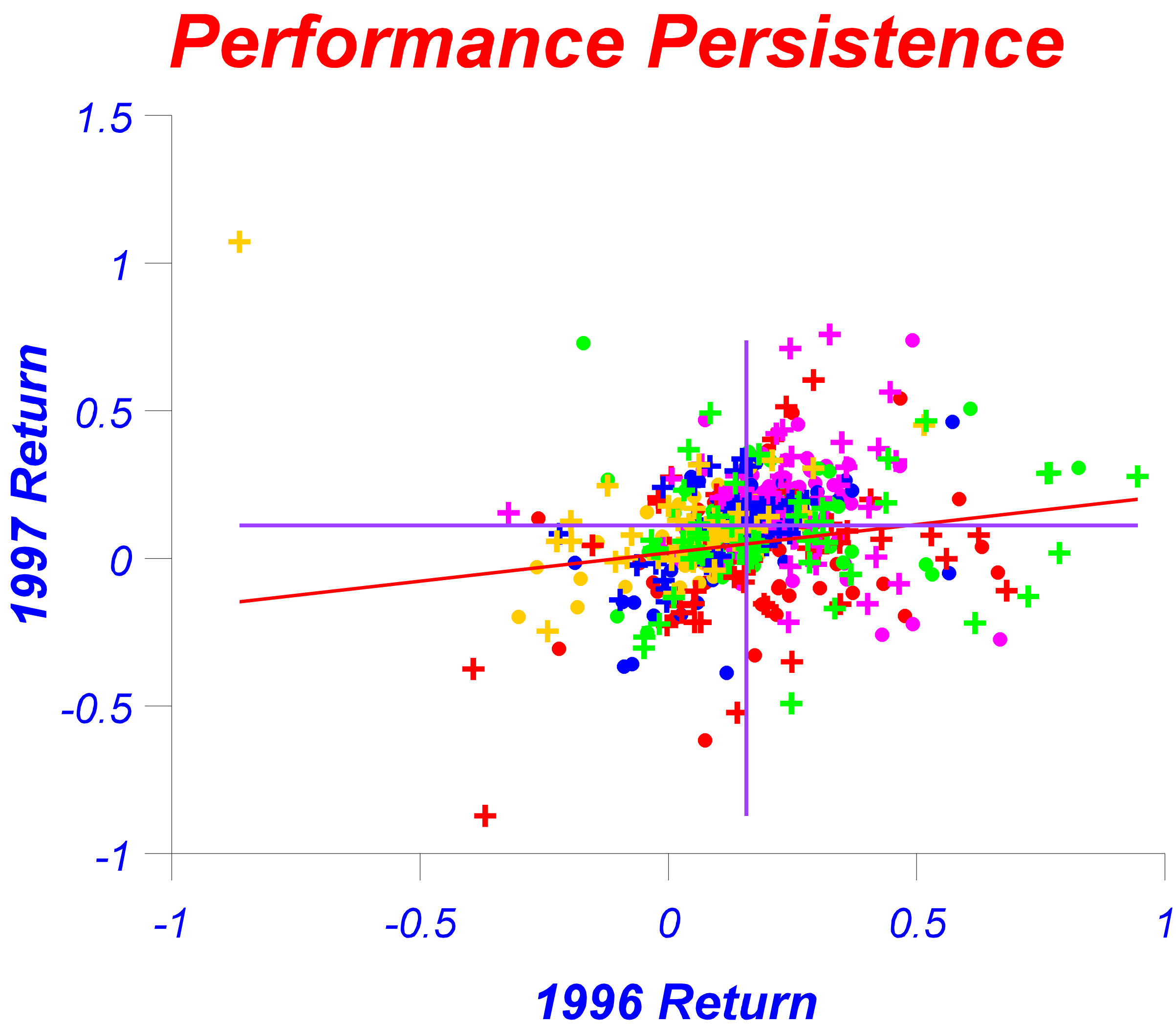
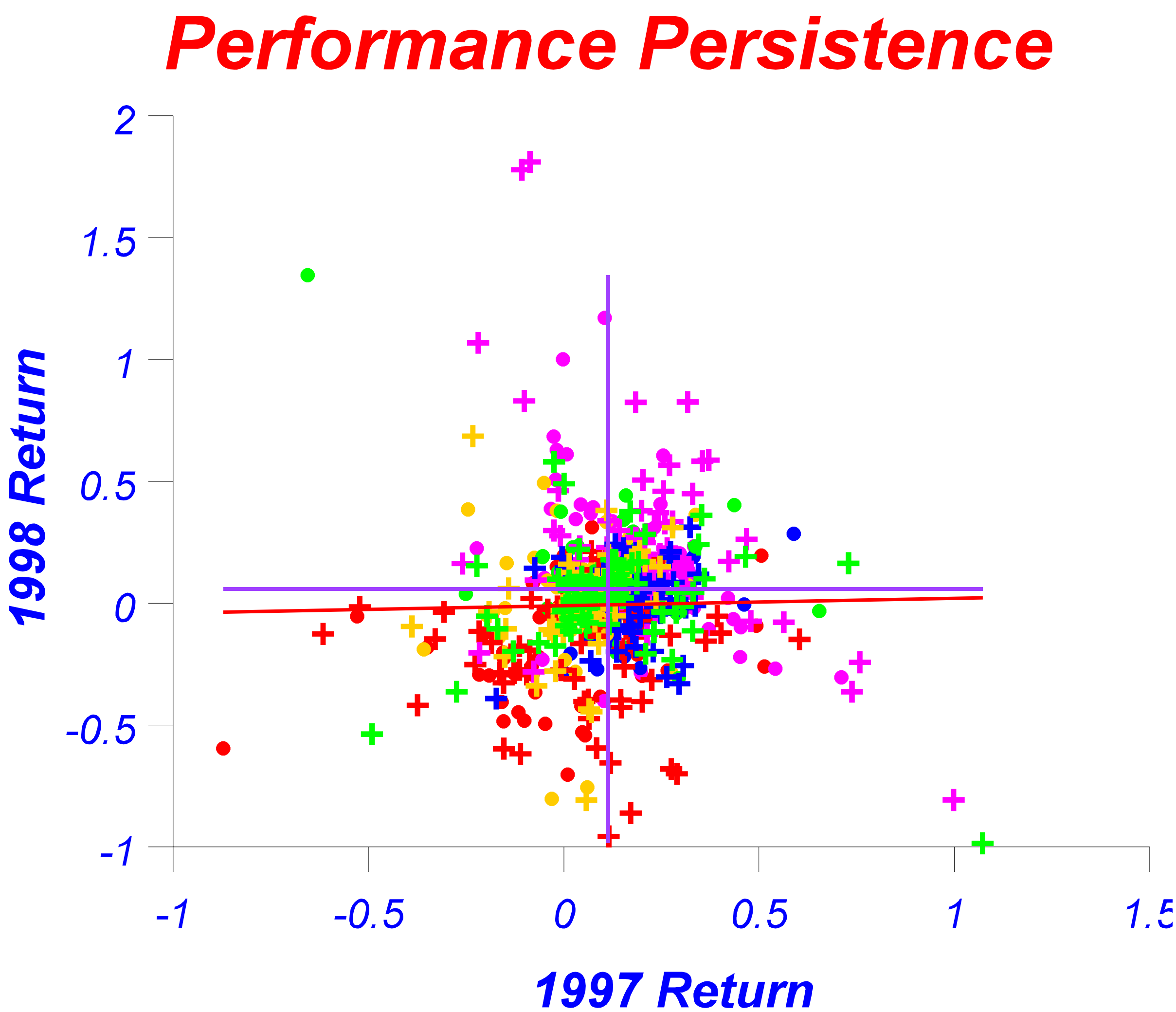
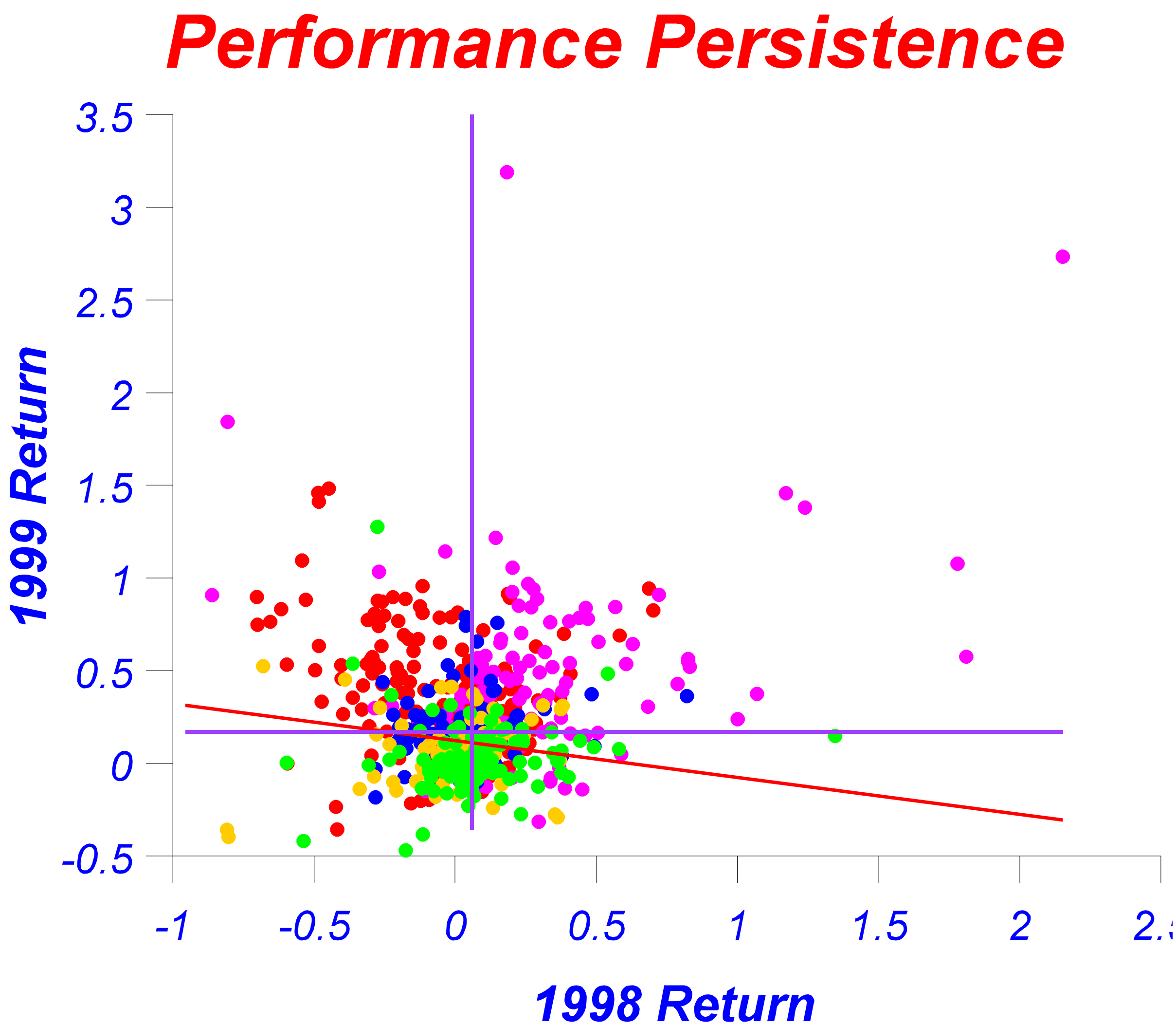

Performance Persistence
1.5
1
0.5
0
-0.5
-1
1997 Return
-1
-0.5
0
0.5
1
1996 Return

Figure 6



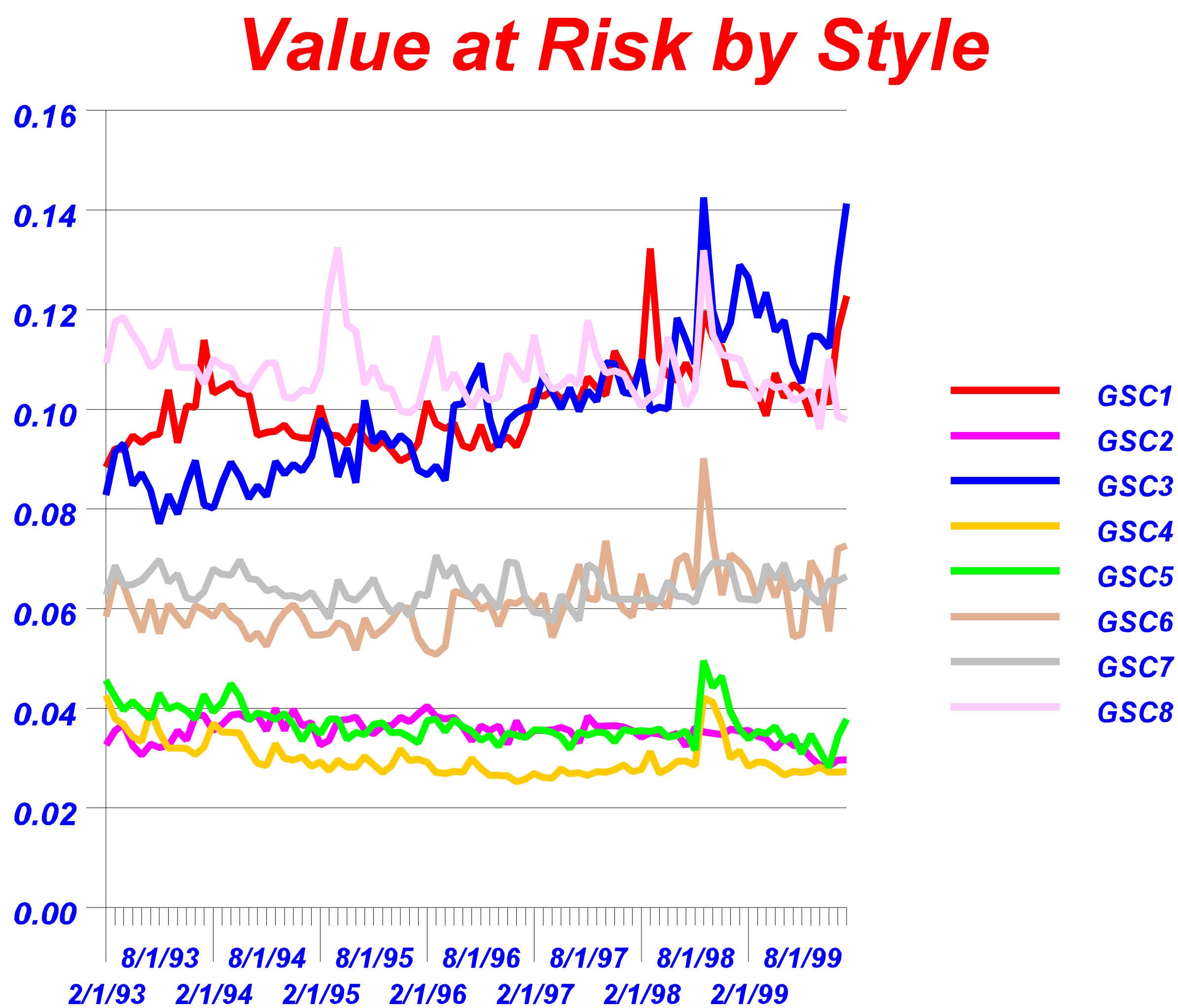
Performance Persistence
2
1.5
1
0.5
0
-0.5
-1
1998 Return
-1
-0.5
0
0.5
1
1997 Return

Figure 7



Performance Persistence
3.5
3
2.5
2
1.5
1
0.5
0
-0.5
1999 Return
-1
-0.5
0
0.5
1
1.5
2
1998 Return

Figure 8


Value at Risk by Style
0.16
0.14
0.12
0.10
0.08
0.06
0.04
0.02
0.00
8/1/93
8/1/94
8/1/95
8/1/96
8/1/97
8/1/98
8/1/99
2/1/93
2/1/94
2/1/95
2/1/96
2/1/97
2/1/98
2/1/99
GSC1
GSC2
GSC3
GSC4
GSC5
GSC6
GSC7
GSC8