

# Predicting Hedge Fund Fraud

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## *Abstract*

Recent cases of hedge fund fraud have revived the debate over appropriate oversight of the industry. One important question is whether regulators have the ability to protect investors by preventing fraud. This paper examines the information content of suspicious patterns in fund returns. We find that the patterns exist in funds subsequently prosecuted by the SEC at the same frequency as in other funds, suggesting that performance data is not useful for predicting fraud. The sensitivity of capital flow to performance, however, is significantly stronger for the former group, indicating that some investors have the ability to distinguish between the two sets of funds.

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## Predicting Hedge Fund Fraud

Widely publicized cases of hedge fund fraud illustrate different ways that unscrupulous managers can harm investors and have revived calls for greater regulatory oversight of the industry.<sup>1</sup> The SEC's 2008 complaint against two Bear Stearns hedge fund managers, for example, charges that they misrepresented the performance of the funds, their exposure to subprime mortgages, and the level of redemption requests. These misrepresentations violate Section 17(a) of the Securities Act of 1933 and Section 10(b) of the Securities Exchange Act of 1934, which prohibit fraudulent practices when offering securities. More brazenly, the \$65 billion Bernard Madoff Ponzi scheme, which lured hedge fund capital through a variety of feeder funds, was built around an entirely fabricated trading strategy. Regulators screen examine funds institutional investors perform due diligence in an effort to identify fraudulent activity before massive losses are incurred. In the wake of recent scandals, this paper asks whether observable indicators of fraud have predictive power.

Indicators of hedge fund fraud can be categorized into operational flags and performance flags. Operational flags are triggered when attributes of a fund's operations and organizational structure, such as integration of service providers and infrequent audits, enable fraudulent activity. Brown et al. (2008) report strong evidence that funds run by managers with prior legal trouble are significantly more likely to bear these operational risks, and are more likely to fail. Performance flags are triggered when attributes of a fund's reported returns, shareholder activity, and asset growth are consistent with fraudulent activity. We focus on performance flags that can be checked on large-scale databases using quantitative algorithms. The purpose of the exercise is to determine the efficacy of a low-cost approach to identifying potentially fraudulent funds, which are then subject to more in-depth examination. Consultancies such as Riskdata employ quantitative filters, but academic evidence is limited.

We study five categories of performance flags, motivated by prior research. These include: (1) a discontinuity in the distribution of a hedge fund's returns, (2) low correlation with systematic risk factors, (3) serial correlation, (4) conditional serial correlation, and (5) the

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<sup>1</sup> On January 20, 2009, Senators Charles Grassley (R-IA) and Carl Levin (D-MI) introduced the Hedge Fund Transparency Act, which, if enacted, will close previous loopholes allowing hedge funds to avoid registering with the SEC.

Riskmetrics quality score. The quality score incorporates the number of returns exactly equal to zero, the number of repeated returns, and several other indicators that returns are misreported. In each case we design appropriate statistical tests for significance. The primary research question we ask is whether funds associated with fraudulent activity or some other regulatory violation are more likely to trigger these flags than other funds. If so, then the flags could be used to predict future trouble, aiding both the investigative efforts of regulatory authorities as well as the due diligence performed by institutional investors.

To determine whether the performance flags are predictors of fraud, we first construct a sample of funds that have been the subject of SEC enforcement actions, which we label “SEC funds.” Next, we assess whether the performance flags are triggered on each hedge fund in a large sample drawn from the TASS and CISDM databases. Then we measure whether SEC funds are more likely to trigger the performance flags than other funds. For almost all of the performance flags, the frequencies with which they are triggered are statistically indistinguishable across the two groups. Furthermore, the percentage of SEC funds that triggers a flag is below 33% in all cases. These results suggest that actual examinations may be necessary to identify funds with a heightened risk of fraud, which may only be possible with a significant investment in resources for regulators. Alternatively, if additional regulation includes mandatory disclosure of operational risks, of the type studied by Brown et al. (2008), then investors and regulators may be able to predict trouble, as these variables have been linked to premature fund closure.

Our last analysis studies whether investors have any ability already to identify funds at greater risk for fraud by comparing the flow-performance relation in all funds to the flow-performance relation in the SEC sample. After controlling for known determinants of fund flow, we find a convex relation in all funds, which is consistent with prior literature. Superior performance is rewarded with large inflows whereas inferior performance is only slightly penalized by outflows. More importantly, outflows in poor performers are substantially higher for the SEC sample, providing managers of these funds with a strong incentive to avoid reporting losses. This result indicates that investors have some ability to detect fraud, but only exit these funds when their performance is weak.

The rest of the paper is organized as follows. In Section I we review related literature. In Section II we discuss the set of quantitative screens used in the study and provide implementation details. Section III describes the data. Section IV presents the results. Section V offers concluding remarks.

## **I. Prior research**

Two strands of prior research are closely related to our study and help motivate our analysis. In subsection A we discuss methods of modeling the failure rate of hedge funds as well as predicting fund failures. In subsection B we explain the incentive for managers to misreport returns and empirical evidence that this practice is not uncommon.

### *A. Fund failures*

Brown et al. (2001) study the attrition rate of hedge funds and commodity trading advisors in the TASS database, augmented with hand collected data, using data from 1989 to 1998. Hedge funds are dropped from the database at a rate of 15% per year, resulting in a half-life of 30 months. Even more extreme, the CTA attrition rate is 20% per year, resulting in a half-life of only 24 months. Using both probit and Cox semiparametric hazard rate analyses, Brown et al. find that low returns and high volatility increase the probability of termination. This result suggests that career concerns offset the performance-based incentives for managers to increase risk.

Gregoriou (2002) studies fund failures in the Zurich Capital Markets database from 1990 to 2001 using several statistical techniques including the Kaplan-Meier estimator of the survival function. He reports that hedge funds have a half-life of 5.5 years and funds of funds have a half-life of 7.5 years, significantly longer than found by Brown et al. (2001). Failure rates peak at age two or three years, and then decline with fund age. He shows that poor performance accelerates in the six months preceding fund failures, and that larger funds and those with higher incentive fees have lower failure rates than other funds. Grecu et al. (2006) test a variety of parametric models of the hazard function, concluding that the log-logistic distribution fits the data best. This distribution results in an inverted U-shaped hazard function, and empirical estimates suggest that

failure rates increase until age 6. Liang and Park (2008) argue that prior estimates of failure rates are overstated because funds may stop reporting, and so be listed as defunct funds, for reasons other than poor performance. For example, superior funds which have exhausted capacity may close to new investment and so no longer need to report returns to attract new partners. They distinguish funds which stop reporting due to failure from funds which stop reporting for other reasons by examining performance and capital flows leading up to the date on which reporting ceases. The resulting “real” attrition rate is 3.1% per year. Liang and Park (2008) also show that downside risk measures dominate volatility as predictors of failure.

Brown et al. (2008) focus not on performance risk measures, but rather on operational risk measures, which relate to “the risks of failure of the internal operational, control, and accounting systems; failure of the compliance and internal audit systems; and failure of personnel oversight systems, that is, employee fraud and misconduct.” The authors gather data from a one-time surge in filings of Form ADV by hedge fund managers in response to the SEC’s short-lived reinterpretation of the 1940 Investment Advisor Act. Data include revelation of any past legal or regulatory problems on the part of management or related advisors, as well as other items related to conflicts of interest, ownership structure, and use of leverage. The authors first separate funds into “problem funds” and “non-problem funds” as determined by whether the manager admitted to any prior legal or regulatory problem. There are 368 problem funds in their sample of 2,299. Next, the authors report how problem funds differ from non-problem funds along a variety of dimensions related to external conflicts of interest, internal conflicts, and ownership or capital structure. In all cases a significantly larger percentage of the problem funds trigger these other operational risk flags than the non-problem funds.

Since the U.S. Court of Appeals overturned the SEC rule changes requiring many managers to register as advisers, and submitting the Form ADV, it is unclear whether operational risk variables will be widely available in the future. For this reason, Brown et al. (2009) use canonical correlation analysis to develop an instrument for operational risk, labeled the  $\omega$ -score, using commonly observable data on fund performance, size, age, and fees. The  $\omega$ -score is a linear combination of these variables that is maximally correlated with the Form ADV information. In Brown et al. (2009), the authors show that the  $\omega$ -score tends to increase the

failure rate of funds in the context of a Cox hazard rate analysis, where fund failure is defined as when the fund stops reporting to the database and subsequently is classified as defunct.

In the same spirit of Brown et al. (2008), our paper maps observable fund information into the likelihood of fund failure. There are two primary differences. First, though Brown et al. (2009) show that their proxy for operational risk is associated with fund failure, they do not distinguish failure due to poor performance from failure due to fraud. Our definition of failure is neither the date that a fund stops reporting nor its classification as a defunct fund in the database, but rather a subsequent regulatory enforcement action. Second, we search for patterns in fund returns that indicate purposeful misreporting, and use the presence of these anomalies as predictors of subsequent fraudulent activity. In contrast, Brown et al. (2008) show that past legal trouble is correlated with the presence of conflicts of interest, concentrated ownership, and poor performance. It might be the case that past legal trouble raises the probability of subsequent enforcement actions, but this is not tested in their paper.

### *B. Misreporting returns*

Prior hedge fund research motivates our study by showing that managers have an incentive to report the most attractive return series possible, and that managers have discretion over trading strategies and reporting practices to affect the shape of the distribution of reported returns.

Managers have an incentive to report attractive return series because their compensation is tightly related to the level of assets under management, and investors are performance-sensitive. Goetzmann et al. (2003) find a positive relation between capital flow and lagged return at the annual frequency for the worst-performing quintile and a negative relation for the best-performing quintile. This result can be explained by investors fleeing bad funds and managers restricting access to good funds. Ding et al. (2008) study the impact of share restrictions, including subscription waiting periods and closure to new investment, on the flow-performance relation in hedge funds. They find that in the absence of restrictions, the relation is convex, whereas in the presence of restrictions, it is concave, consistent with the results in Goetzmann et al. (2003).

Goetzmann et al. (2007) point out that if investors use scalar performance measures, such as the Sharpe ratio or Jensen's alpha, to select managers, then managers have an incentive to take actions to enhance these measures, including manipulation of the performance measures through "information-free" trading activities. The authors show how traditional measures can be distorted through simple manipulation strategies, and devise a performance measure that is not subject to the same type of manipulation. Note that the authors do not consider misreporting or other types of misrepresentation – they instead focus on trading strategies that are conducted to affect the return distribution of a fund in specific ways to game standard performance measures. In addition to manipulating returns through trading, managers can affect the distribution of reported returns by deciding when to report returns to a database. Ackermann et al. (1999), Brown et al. (1999), and Liang (1999) show how the reporting decision can generate biases in hedge fund databases, including survivorship bias and backfill bias. In contrast to all of these studies, we examine indicators that predict when reported returns are themselves distorted.

Liang (2003) examines the quality of self-reported hedge fund return data by comparing returns of funds that report to both the TASS Management Ltd. database and the U.S. Offshore Fund Directory. He finds an average absolute difference in annual returns of 8.83% for funds with incomplete audit information and 4.91% for funds with complete audit information, suggesting that regular audits increase the quality of hedge fund data. Liang (2003) does not study whether errors are more pronounced when managers have higher incentives to misreport; nonetheless his results show that there is significant opportunity for returns to be manipulated.

Prior research has uncovered some evidence that some managers purposefully misreport returns, presumably in an effort to attract and maintain their investor base. Several of these studies introduce some of the quantitative filters which we discuss in more detail in the next section. Getmansky et al. (2004) show that managers who report moving averages of fund returns generate artificially low volatility and high Sharpe ratios. Bollen and Pool (2008) argue that the resulting serial correlation will likely be higher during times of low performance, since managers have the incentive of delaying reporting losses but fully reporting gains. They develop a conditional serial correlation measure to incorporate the asymmetry in incentives. Agarwal et al. (2007) find that hedge fund returns are higher in December than other months, suggesting that managers inflate year-end returns to game incentive systems, similar to the year-end anomaly in mutual fund returns in Carhart et al. (2002).

The accounting literature has produced several studies that examine episodes of corporate scandal and SEC enforcements, and their relation to quantitative filters constructed from accounting statement ratios. These accounting anomalies are analogous to the predictors of hedge fund fraud based on suspicious patterns in reported returns, which we describe in the next section. Corporate earnings management bears strong similarities to the misreporting of hedge fund returns. Beneish (1999) constructs a sample of 74 companies that manipulated earnings in the 1987 to 1993 period as reported in either the SEC's Accounting and Auditing Enforcement Releases or the news media. He identifies five accounting measures that are significantly related to the incidence of earnings management. Grove and Cook (2004) examine the 10-K's of Enron, WorldCom, Global Crossing, and Qwest in the year prior to the public dissemination of the firms' accounting scandals. The authors measure a wide variety of quantitative red flags to determine which are best able to identify subsequent problems – two of which are established in Beneish (1999).

## **II. Quantitative Screens for hedge fund fraud**

This section describes the five categories of performance flags we use to indicate a higher probability of fraud. A discussion of the motivation for each flag is provided, as well as details of the statistical tests we use to determine when the flag is triggered.

### *A. Discontinuity at zero*

Hedge funds are sometimes described as absolute-return vehicles that strive to deliver positive returns regardless of market conditions, as in Waring and Siegel (2006). Investors appear to value this property. As shown by Bollen and Pool (2009) and Agarwal et al. (2007), hedge fund investors direct capital towards managers who have reported a higher number of positive monthly returns, even after controlling for the level of cumulative return. If managers are able to deliver mostly positive returns through skill, then counting the number of losses would be a reasonable way to identify ability. However, evidence suggests that loss-avoidance

might be evidence of misreporting.<sup>2</sup> Bollen and Pool (2009), for example, show that the distribution of hedge fund returns, when pooled in the cross-section and in the time series, features a sharp discontinuity at zero. The discontinuity disappears when returns are computed at the bimonthly frequency instead, indicating that some returns are inflated then reversed to avoid reporting losses. Thus, our first flag for fraud is triggered when the distribution of a hedge fund's reported returns features a significant dearth of negative returns.

Bollen and Pool (2009) develop a statistical test for a discontinuity in the distribution of hedge fund returns that requires a reference distribution constructed using a kernel density estimator. They study the pooled distribution of returns, and so have sufficient data to construct the reference distribution, even for subsets of funds. However, this procedure is not feasible for testing individual funds. Instead, we adopt the approach of Burgstahler and Dichev (1997). For each fund, we first create a histogram of reported returns. Following Silverman (1986), we use an optimal fund-specific bin size given by

$$(1) \quad \alpha \times 1.364 \times \sigma \times N^{-\frac{1}{5}}$$

where  $\alpha$  is a distribution-specific constant,  $\sigma$  is monthly return standard deviation, and  $N$  is the number of observations. We set  $\alpha = 0.776$ , corresponding to a normal distribution, since Devroye (1997) shows through simulation that the calculation is robust to alternative distributional assumptions. We then count the number of return observations that fall in three adjacent bins, two to the left of zero and one to the right. Under the null hypothesis of a smooth distribution, the number of observations that fall in the middle bin should be approximately equal to the average of the surrounding two bins.

We construct a simple statistical test for a discontinuity in the distribution at zero based on binomial probabilities. Let  $p_1$ ,  $p_2$ , and  $p_3$  denote the probability that an observation falls in each of the three bins, where  $p_2$  corresponds to the middle bin. The test statistic for determining whether  $p_2$  is significantly different from the average of  $p_1$  and  $p_3$  is the difference between the actual number of observations in the middle bin and the expected number, divided by the

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<sup>2</sup> Harry Markopolos, the CFA who presented evidence of the Madoff Ponzi scheme to the SEC beginning in 2000, describes in his 2009 testimony to the U.S. House of Representatives how investors were lured by its steady return stream, with only three monthly losses in an 87-month span.

standard deviation of the difference. As shown in the appendix, the variance of the difference can be expressed as:

$$(2) \quad N(p_2 - p_2^2) + \frac{1}{4}N(p_1 - p_1^2 + p_3 - p_3^2) + Np_2(p_1 + p_3) - \frac{1}{2}Np_1p_3$$

Note that this calculation takes into account the covariance between bins that naturally arises, since if a given observation falls in one of the bins it cannot lie in the others. Our flag is triggered when the number of observations in the middle bin is significantly less than expected at a 5% significance level.

### *B. Low correlation with other assets*

One purported benefit of hedge fund investment is diversification due to a low correlation with standard asset classes. Fung and Hsieh (1997), for example, report that about half the funds in their sample feature an R-squared below 25% in factor model regressions with eight factors capturing exposure to equities, bonds, and commodities. There are several sources of this low correlation. Some funds hedge exposure to systematic risks by holding long and short positions in different securities. Other funds engage in high-frequency dynamic trading that generates nonlinear and time-varying correlation to systematic risks. Researchers have developed “style factors” which attempt to mimic well-known hedge fund trading strategies to provide risk measurement and performance appraisal even when funds have low correlation with standard asset classes.<sup>3</sup>

As argued by Sun et al. (2009), managers with skill and informational advantages likely pursue profitable trading strategies that are different from those followed by other managers; hence low correlation with funds in the same category could be a predictor of abnormal performance. Indeed, the difference between the subsequent one-year returns of top and bottom quintiles of funds sorted by their strategy distinctiveness index, which equals one minus the correlation between a fund’s returns and the average returns of funds in the same category, equals over six percent. Similarly, Titman and Tiu (2008) find that hedge funds in the lowest quartile, as ranked by adjusted R-squared of factor model regressions, have the highest

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<sup>3</sup> See, for example, Fung and Hsieh (2001), Agarwal and Naik (2004), and Bollen and Whaley (2009)

subsequent Sharpe ratios. These results suggest that funds tend to succeed when their returns are less correlated with other funds and with common style factors.

Note, however, that if a manager misreports returns, his fund may also feature low correlation with standard asset classes, hedge fund style factors, and even funds in the same category. A manager who reports a random positive return every month will artificially generate a correlation between the fund's returns and any other time series very close to zero. Harry Markopolos notes in his 2009 testimony that Madoff's returns had a correlation of only 0.06 with the S&P 500, whereas the supposed split-strike conversion strategy should feature a correlation close to 0.50, and this low correlation signals fraud in "flashing red letters." Thus, we use low correlation with a set of style factors as an indicator of fraud.

We measure the uniqueness of a fund's return series by estimating the correlation between the fund's returns and those of a set of style factors. We run, for each fund, a regression of fund returns on every possible subset of factors and record the maximum achieved adjusted R-squared, which we label *maxrsq*. We limit the number of factors used in a given regression to three, corresponding to the three most prominent strategies a fund follows. Then we assess whether the *maxrsq* is significantly different from zero. We generate critical values for *maxrsq* under the null hypothesis that fund returns are random.<sup>4</sup> For each fund, we randomly generate a vector of standard normal returns with length equal to the fund's history. Then we choose the optimal subset of factors using the same set of factor returns used for the actual fund to determine the *maxrsq* for the randomly generated data. We repeat the procedure 100 times: the percentiles of the resulting 100 *maxrsq* serve as critical values for the actual fund. If an actual fund's *maxrsq* is smaller than the 90<sup>th</sup> percentile of the randomly generated data, then we fail to reject the null hypothesis that the returns are random and the low correlation flag is triggered.

### *C. Unconditional serial correlation*

Getmansky et al. (2004) argue that when hedge funds are invested in illiquid securities, returns can feature low volatility and positive serial correlation. A possible reason for this result is that portfolio values reflect new information gradually over time as managers conservatively

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<sup>4</sup> Foster, Smith, and Whaley (1997) develop critical values for the maximal R-squared in asset pricing models.

update model values. They measure serial correlation in residuals and find that funds invested in more illiquid securities, such as emerging market debt, feature higher serial correlation than other funds. Another explanation for this result is that some managers are purposely smoothing returns by reporting moving averages of current and lagged portfolio returns. Working (1960) shows how moving averages feature lower volatility than raw observations, and will possess serial correlation even when raw observations have none.

We regress fund returns on their first lag to test for unconditional serial correlation:

$$(3) \quad R_t^o = a + bR_{t-1}^o + \varepsilon_t$$

where  $R_t^o$  represents a fund's observed return at date  $t$ , to indicate that it is potentially different from the actual return of the fund. A positive coefficient significant at the 5% level is required to trigger this flag for suspicious returns.

#### *D. Conditional serial correlation*

The ability for managers to misreport by smoothing is increasing in the illiquidity of the assets they hold, since the opportunity to exercise discretion exists only when recent trade prices are not available. Thus Getmanky et al. (2004) are careful to point out that since marking-to-model and deliberate smoothing generate identical time series properties, it is difficult to make a statement about a manager's intent without additional information. Alternatively, Asness et al. (2001) and Bollen and Pool (2008) suggest additional econometric techniques that attempt to distinguish innocuous behavior from purposeful misreporting. We adopt the procedure in Bollen and Pool (2008) which is based on the premise that managers have an incentive to smooth losses to delay reporting poor performance, and an incentive to fully report gains in their competition for investor capital. As a consequence, the amount of serial correlation varies conditional on the magnitude of lagged returns.

To test for conditional serial correlation, the distinction between a fund's observed return  $R_t^o$  on date  $t$  and the actual return of the fund's portfolio  $R_t$  is important. We make the assumption that the degree of smoothing, and hence serial correlation, is a function of the actual lagged return  $R_{t-1}$ . Of course the actual return of a fund is unobservable, hence we proxy for it

by using the fitted value of the optimal factor model constructed above. As in Bollen and Pool (2008), we regress observed returns on their lag with an interaction term as follows

$$(3) \quad R_t^O = a + b^+ R_{t-1}^O + b^- (1 - I_{t-1}) R_{t-1}^O + \varepsilon_t$$

where  $I_{t-1} = 1$  if the fitted value of observed returns in month  $t-1$  is greater than its mean and zero otherwise. Thus,  $b_1^-$  measures the incremental serial correlation following poor returns; a positive coefficient means that serial correlation is higher, which is consistent with an avoidance of reporting losses. Positive coefficients significant at the 5% level are required to trigger this flag for suspicious returns.

#### *E. Riskmetrics quality score*

Straumann (2008) investigates the quality of hedge fund return data, in the spirit of Liang (2003), without taking a strong stand on the motives behind any “man-made” patterns that are revealed by his analysis. He examines each fund’s return history and attempts to detect five patterns. The fund’s quality score is then recorded as the number of patterns present, with a higher score indicating lower quality. The five patterns are: (1) too many returns exactly equal to zero, (2) too few unique returns, (3) too long a string of identical returns, (4) too many recurring blocks of length two, and (5) a distribution of the second digit after the decimal that rejects the null of uniform.

Straumann finds that funds of funds have the best data quality, with an average score of 0.23, hedge funds come next, with an average score of 0.35, and CTAs feature an average score of 0.45. He attributes the high score for CTAs to the large number of small CTAs included in the Barclay database he uses. Another predictor of data quality is whether a fund is listed as being audited. The average score of audited CTAs with time series length greater than six years is 0.40, for example, compared to 0.70 for non-audited CTAs.

The consequences of low quality data are unclear. Straumann shows that the impact on average annual return is 16 basis points for CTAs, compared to 175 basis points for survivorship bias. However, funds with better quality data appear to feature less of discontinuity at zero, suggesting that poor data quality is indicative of an attempt to make a fund’s time series more

appealing to investors. While the five patterns described are not necessarily cause for concern, their presence could be an indicator of more harmful actions.

Rejection regions for the tests are affected by a variety of fund attributes including the length of the time series, properties of the return distribution, and rounding conventions for reported returns. For example, the expected number of zero returns and the expected maximum string of identical returns are both increasing in the length of the time series and the size of the minimum return increment. To control for the length of the time series, we record the number of zeroes and the number of unique returns as the percentage of the sample. Reported returns in actual hedge fund data are most often reported to the nearest hundredth of a percent, but a substantial number report to the nearest ten thousandth.

Critical values for the five tests are obtainable analytically. For example, under the assumption that true returns are distributed  $N(\mu, \sigma^2)$ , the probability  $p$  that a given return is reported as 0.0000 for a fund that rounds to the nearest basis point is given by:

$$(4) \quad p = \int_{-0.00005}^{+0.00005} \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2} dx$$

and hence the probability  $\bar{p}_{k,n}$  of observing  $k$  zeroes in a series  $n$  observations long is equal to:

$$(5) \quad \bar{p}_{k,n} = \binom{n}{k} (1-p)^{n-k} p^k$$

We can reject the null hypothesis at an  $\alpha$  significance level if the observed number of zeroes  $k$  satisfies:

$$(6) \quad \sum_{i=k}^n \bar{p}_{i,n} < \alpha$$

It is clear from this example that critical values are affected by the underlying return distribution, the rounding convention, and the length of the time series. Obtaining critical values for the other tests is challenging, especially given the impact of rounding, and so we establish critical values through Monte-Carlo simulation over a range of attributes, in the same spirit of Straumann (2008).

We begin by generating 10,000 series of 240 draws from a standard normal distribution, reflecting 20 years of monthly returns. We then scale the variates over a range of means and volatilities, allowing the annual mean to range from 5% to 25% in increments of 5%, and the annual volatility to range from 5% to 50%, also in increments of 5%. We then form four different sets of random data by rounding to the nearest tenth, hundredth, thousandth, and ten thousandth of a percent. For each series, we then compute and record the values of the five test statistics. The extreme percentiles of the resulting distribution of test statistics provide critical values under the null hypothesis that returns are reported accurately.

### **III. Data**

The hedge fund data used in our analysis are drawn from the Center for International Securities and Derivatives Markets (CISDM) and the Lipper TASS (TASS) databases. The sample period is from January 1994 through December 2008. Returns are net of all management and performance-based fees, including the fees charged by funds of funds managers. Both databases include live and defunct hedge funds, funds of funds, and commodity trading advisors. We focus on live and defunct hedge funds, since these constitute the vast majority of SEC enforcement actions. The CISDM data also include index funds which we discard, since their returns are composites of individual funds whereas our interest is at the fund level. A fund must have at least 24 contiguous monthly observations of returns that overlap with the sample period for the factor returns, January 1994 through September 2008, to be included in our analysis.<sup>5</sup> Some fund managers report returns to both databases, so we check for matches and delete duplicates. First, potential matched pairs are formed by examining the names of funds in the two databases. Since these potential matched pairs have names that are often not identical, though very similar, we then compute the correlation between the return series of each pair of funds. Pairs with correlation above 99% are deemed matches and the series with the shorter history is discarded. After deleting duplicates, there are 8,770 funds in our sample: 3,039 hedge funds from the CISDM database, with 216,207 observations, and 5,731 funds from the TASS database, with 418,468 observations.

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<sup>5</sup> We also discard 16 TASS funds and 7 CISDM funds with at least one monthly return observation greater than 200%, likely the result of database errors.

We collect a set of 14 factors that are used in the existing hedge fund literature to proxy for the trading strategies employed by hedge fund managers. These factors are drawn from three sources. The three Fama-French factors, the excess return of the market and the returns of size and value portfolios, as well as the momentum factor, are from Kenneth French's website. We also include the squared returns of the size, value, and momentum factors to capture nonlinearities in exposure generated by derivatives or dynamic trading. Five trend-following factors, which are the returns of portfolios of options on bonds, foreign currencies, commodities, short-term interest rates, and stock indexes, are obtained from David Hsieh's website. The change in the yield of a ten-year Treasury note and the change in the credit spread, defined as the yield on ten-year BAA corporate bonds less the yield of a ten-year Treasury note, are obtained from the U.S. Federal Reserve's website. To estimate the factor model, we also require a risk-free rate, and for this we use the one month T-Bill rate from Kenneth French's website.

Our primary research question is whether funds with return series that feature particular patterns are more likely to be subsequently prosecuted by the SEC. We hand collect information regarding 158 SEC prosecutions from SEC litigation releases available on the SEC website.<sup>6</sup> We place them into seven categories: "Misappropriation," "Overvaluation," "Misrepresent returns," "Ponzi," "Short Sale Violation," "Insider Trading," and "Other." We place funds in the "Other" category if they do not fit any of the first six groups. Figure 1 shows the number of enforcement actions in our sample that were filed in each of the years 1997 through 2009. The number increases over time, consistent with the growth of the industry, though it constitutes a tiny fraction of the number of hedge funds in existence. We match hedge funds mentioned in the litigation releases to our return data. Of these, 93 have sufficient data to be in our final sample, and these constitute the SEC funds.

Table 1 lists the number of fraud cases, and associated funds in our sample, which fall into each category. The total number of cases exceeds 158 because some cases involve multiple offences. Similarly, the number of funds exceeds 93 because some funds are associated with cases involving multiple offences. While the litigation reports often describe extreme behavior, such as stealing fund assets or reporting wildly inflated asset values, the reporting peculiarities

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<sup>6</sup> We use the search engine found in the Litigation section of [www.sec.gov](http://www.sec.gov) and search using the term "hedge fund." All matches are then checked manually to determine if they relate to an enforcement action against a hedge fund manager.

we study do not necessarily endanger investors to the same degree. Furthermore, not all of the violations involve fraud, e.g. violations of short sale rules. We decide not to make a distinction for the purposes of this study, since the question is whether the presence of a suspicious statistical footprint increases the likelihood that some other malfeasance subsequently occurs and is detected.

As shown in Getmansky et al. (2004), the returns of illiquid fund types often feature different time series properties than the returns of liquid fund types, including positive serial correlation. Other quantitative filters may vary across fund types; hence we extract fund strategies from the CISDM and TASS databases. Table 2 lists 13 categories of styles created from the two databases, as well as the number of funds in each category, both in the full sample and SEC sample. Approximately half the funds are in the Equity Long/Short and Equity Market Neutral categories, which are highly liquid.

Table 3 lists summary statistics of the 93 SEC funds (Panel A) and all other funds in the hedge fund sample (Panel B). Listed are the number of funds and equally-weighted cross-sectional averages of each fund's monthly average return, standard deviation, Sharpe ratio, skewness, excess kurtosis, and first-order serial correlation. Also listed is the number of funds with serial correlation coefficients significant at the 5% two-sided level, separated by sign.

In both Panel A and Panel B, live funds feature substantially lower average returns and Sharpe ratios than defunct funds. Live SEC funds, for example, have average monthly return of 0.88% versus 1.24% for defunct funds; all other funds have average monthly return of 0.52% when live and 0.73% when defunct. This is at first surprising, as anecdotal evidence suggests that hedge fund investors withdraw capital en masse, and many hedge funds ultimately shut down, following periods of poor performance, so that defunct funds have lower returns. Note though that the live funds' statistics are heavily influenced by their poor performance in 2008, whereas most defunct funds left the databases by then. Given the historic growth of the industry, any sample of live hedge funds will be largely populated by new funds; hence the average return of live funds will be heavily influenced by the most recent period. To investigate this further, we compute the cross-sectional average return of live and defunct funds month-by-month, displayed in Figure 2. The two series track each other quite closely, with the exception of the NASDAQ stock market crash of late 2000 and the global meltdown of late 2008. This result suggests that

defunct funds may not necessarily have been run by inferior managers, but were rather simply unlucky during highly volatile episodes.

More importantly, SEC funds feature substantially higher average returns than other funds. Overall, for example, the 93 SEC funds deliver 1.13% per month versus 0.64% for all other funds. Sharpe ratios tell the same story, with the SEC funds averaging 0.3139 versus 0.1411 for all other funds. The differences are statistically significant, indicated by the  $p$ -values for a standard two-sample  $t$ -test listed below the summary statistics in Panel B. This result suggests that superior performance may be an indicator of fraud. To control for other determinants of performance, we construct a control group by matching each SEC fund with 10 funds in the non-SEC sample. First, for each SEC fund, we determine potential controls by matching on live/defunct status, style, and time period. Funds are classified as equity if they are in the long/short equity or equity market neutral styles; equity (non-equity) SEC funds are matched with all other equity (non-equity) funds. The time periods of two funds match if their first dates are within 24 months of each other, and if their last dates are as well. Next, we compute pair-wise correlations with all potential matches, and pick the 10 funds with the highest correlation. Not counting duplicates, there are 630 funds in the control group. Their results are listed in Panel C. Again, the SEC funds have significantly superior performance.

All categories feature substantial excess kurtosis, consistent with option-like payoffs in the strategies they employ, motivating Fung and Hsieh (2001, 2002, 2004) to use baskets of traded options to mimic strategy returns. However, the defunct SEC funds have dramatically higher excess kurtosis than all other funds, 10.6689 versus 4.1507. Furthermore, while live SEC funds feature positive skewness, 0.3872 versus -0.6630 for all other live funds, defunct SEC funds feature negative skewness of -0.8008 versus -0.2158 for all other defunct funds. These results suggest that when SEC funds become defunct, they tend to feature large, negative returns relative to all other funds.

These preliminary results show that the reported returns of SEC funds exhibit pronounced differences from the full sample. The next section determines whether they differ as well in their tendency to trigger quantitative flags for suspicious activity.

## IV. Results

### A. Flag frequency

Our main results are displayed in Table 4. Listed for each performance flag are the percentages of SEC funds, all other funds, and the control group that trigger it. Also listed are  $p$ -values from standard tests for a difference in proportions between the rejection rate of SEC funds and the other two groups. An ideal performance flag would be triggered for a high percentage of the SEC sample, thereby minimizing Type I error, and a low percentage of the other samples, resulting in a low Type II error as well. None of the flags display this property. The highest rejection rates for SEC funds are 24.7% for the “%Unique” test, 31.2% for the “Uniform” test, and 32.3% for the “CAR(1)” test. This result suggests that Type I error is substantial. More worrisome still, the rejection rates are statistically indistinguishable from the corresponding rates in all other funds, so that the tests have no ability to distinguish between the two sets of funds.

The only tests which have higher rejection rates for the SEC funds are the *maxrsq* and *kink* tests, which are triggered in 24.7% and 22.6% of the sample, respectively, compared to 13.2% and 14.6%, respectively, for the control group of funds. These results suggest that funds prosecuted by the SEC are somewhat more likely to feature a discontinuity in returns, and low correlation with other assets, than we might expect given other fund attributes. Note, though, that in order to form the control group we needed to know *ex ante* which funds to match to, so it is unclear whether these flags would help predict fraud. For more detail on the *maxrsq* test, Table 5 shows the number of funds by history length, the number of times the flag was triggered, the average adjusted  $R$ -squared of the funds, and the average 90<sup>th</sup> percentile critical value for a significant adjusted  $R$ -squared. The rejection rate is much higher for the youngest funds, suggesting that the result may simply be driven by the low number of observations rather than any purposeful misreporting on the part of fund managers.

Though our analysis suggests that performance flags are of little help in predicting fraud, two important caveats are worth discussing. First, our sample of SEC funds likely is a small subset of the actual group of funds suffering from fraudulent activity. Fund managers can also be subject to lawsuits brought forth by the CFTC as well as investors in their funds. We are currently gathering data on other lawsuits to supplement our sample. Furthermore, some fraudulent activity may go undetected. Second, we are including in our SEC sample all funds

that are the subject of SEC litigation releases, regardless of the type of infraction. It might be the case that performance flags help predict some types of violations and not others. Our small sample size prevents examining the relation between performance flags and subsequent violations on subsets.

### B. Flow-performance sensitivity

The performance flags do not appear to help predict which funds subsequently are prosecuted by the SEC. A remaining question is whether due diligence efforts that focus on other information, such as the presence of operational flags, are useful. Rather than specify these, as in Brown et al. (2008), we examine the response of investors to performance, and whether this sensitivity differs across the SEC and non-SEC sample, to determine whether investors are treating the SEC funds differently.

The flow-performance regressions are similar to those in Sirri and Tufano (1998), also adopted in Brown et al. (2008). Percentage flow for fund  $i$  in year  $t$  is calculated as follows:

$$(7) \quad flow_{i,t} = \frac{AUM_{i,t} - AUM_{i,t-1}(1 + R_{i,t})}{AUM_{i,t-1}}$$

where  $AUM_{i,t}$  and  $R_{i,t}$  represent assets under management and the return of fund  $i$  in year  $t$ , respectively. To measure performance, each year we rank each fund using raw returns relative to the funds in its style group and assign the corresponding performance percentile. To estimate the coefficients associated with these percentile ranks, we use a piecewise linear specification with four performance quartiles, with quartile one the best. The four performance variables used in the regression are based on a fund's percentile and defined as follows:

$$(8) \quad \begin{aligned} qrank4_{i,t-1} &= percentile_{i,t-1} - 0.50 \text{ if } 0.00 \leq percentile_{i,t-1} < 0.25 \text{ and } 0 \text{ otherwise} \\ qrank3_{i,t-1} &= percentile_{i,t-1} - 0.50 \text{ if } 0.25 \leq percentile_{i,t-1} < 0.50 \text{ and } 0 \text{ otherwise} \\ qrank2_{i,t-1} &= percentile_{i,t-1} - 0.50 \text{ if } 0.50 \leq percentile_{i,t-1} < 0.75 \text{ and } 0 \text{ otherwise} \\ qrank1_{i,t-1} &= percentile_{i,t-1} - 0.50 \text{ if } 0.75 \leq percentile_{i,t-1} \leq 1.00 \text{ and } 0 \text{ otherwise} \end{aligned}$$

This specification yields coefficients that are easy to interpret. For a given percentile rank, only one coefficient is relevant. Positive coefficients on  $qrank4$  and  $qrank3$  correspond to outflows, whereas positive coefficients on  $qrank2$  and  $qrank1$  correspond to inflows. Positive coefficients

on all four variables of approximately equal magnitude would indicate a linear response of flows to performance, with outflows for below-median funds that are increasing in the distance from the median, and inflows for above-median funds that are increasing in the distance from the median.

We only include observations of flows and returns for SEC funds in the years prior to the filing date of the SEC enforcement actions. This aids in interpreting any differential sensitivity to performance for the SEC funds as being the result of investors' predictive ability, rather than the response to a known accusation.

As in Brown et al. (2008), we also include interaction terms in the regression of the following form  $Xj_{i,t-1} = qrankj_{i,t-1}I_i$ , where  $I_i$  equals one if fund  $i$  is in the SEC subsample and zero otherwise. We use fund size, return volatility (both measured in year  $t-1$ ), contemporaneous average flow to the fund's style group, incentive fee, and management fee as additional explanatory variables in the regression. Fund size is expressed as the log of fund  $i$ 's assets under management measured in US dollars. The flow-performance results below are based on the Fama and Macbeth (1973) method.

Results are displayed in Table 6. Model 1 excludes the interaction terms. Flows are positively related to size and management fee. These results are in contrast to Brown et al. (2008) and Ding et al. (2008), who find negative relations. Controlling for performance, it is natural to expect investors would shift capital to lower fee funds. One explanation for the different results is that our data extend through 2008, whereas their data end in 2005 and 2004, respectively. We show in Table 3 that the low returns of funds in 2008 yield a paradoxical result that live funds feature lower average returns than defunct funds. Similarly, the low returns in 2008 could distort the sensitivity of flows to fees – managers of high fee funds have more of an incentive to prohibit outflows by temporarily invoking redemption restrictions, leading to the positive relation between flows and fees.<sup>7</sup>

Flows are negatively related to volatility, which is consistent with Brown et al. (2008) and Ding et al. (2008), and consistent with risk averse investors. The coefficients on the *qrank* variables are all positive, and all are significant at the 5% level except for *qrank3*. These results indicate a convex relation to performance, in which above-median returns are rewarded with

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<sup>7</sup> See for example, Ang and Bollen (2009).

inflows to a much greater extent than below-median returns are punished by outflows. The coefficient on *qrnk4* is 0.5910, so that the worst performing fund has outflows equal to about  $0.5910 \times -0.50 = -0.30$  or 30% of fund assets resulting from the poor performance. The coefficient on *qrnk1* is 2.1267, so that the best performing fund has inflows equal to about  $2.1267 \times 0.50 = 1.13$  or 113% of fund assets resulting from the superior performance. These results are consistent with Brown et al. (2008) and Ding et al. (2008).

Model 2 adds the SEC interaction terms. The coefficients on interaction terms X1 and X2 are negative but insignificant, so that the SEC indicator does not appear to affect inflows resulting from above-median performance. However, the coefficients on interaction terms X3 and X4 are positive and significant at the 5% level. This result suggests that investors withdraw capital from below-median performers at a much faster rate when the funds are also subsequently prosecuted by the SEC. For funds at the 25<sup>th</sup> percentile, for example, the non-SEC funds do not experience any performance-related fund flow, since the coefficient on *qrnk3* is an insignificant 0.3230. In contrast the SEC funds at the 25<sup>th</sup> percentile would suffer outflows equal to  $1.1179 \times 0.25 = 0.28$  or 28% of fund assets. These results indicate that investors do treat SEC funds differently from other funds, suggesting that they perceive these funds to be a greater risk than other funds.

One interpretation of the heightened sensitivity of flow to poor performance in SEC funds is that investors can use information from their own due diligence efforts to predict fraud. Alternatively, managers of SEC funds might be able to predict the fund's demise and might warn coconspirators, friends, and family to exit the fund. To the extent that this typically occurs when performance wanes, the flow-performance sensitivity would be especially strong for poor performers.

## **V. Conclusion**

The widely publicized, recent cases of hedge fund fraud have raised once more the debate regarding hedge fund regulation. In the past, opponents of a registration requirement argued that additional regulation would act as a hollow promise of safety, since agencies such as the SEC do not have adequate resources to conduct a sufficient number of examinations to prevent and deter fraudulent activity. Furthermore, investors may put forth less effort in conducting their own due

diligence. The goal of this paper is to test whether low-cost pre-screens based on suspicious patterns in returns are effective in predicting which funds subsequently violate SEC law.

We determine whether each fund in a large sample triggers one or more performance flags based on the fund's time series of reported returns. The flags include a discontinuity in the fund's distribution of returns at zero, low correlation with asset and style indexes, serial correlation, and low data quality as measured by the Riskmetrics quality score. Our results indicate that funds subsequently prosecuted by the SEC trigger the flags at roughly the same frequency as other funds, suggesting that pre-screens based on suspicious patterns in returns would not have been effective predictors of hedge fund fraud. We also study whether investor responses to good and bad performance are different for funds subsequently prosecuted by the SEC. Outflows following poor performance are economically and statistically significantly higher for the SEC funds than other funds, suggesting that investors are able to perceive a difference, perhaps due to their own due diligence activity.

From a regulatory perspective, our results may mean that additional regulation must be accompanied by either (1) sufficient additional resources to support wide-spread, ongoing preventive examinations, or (2) requirements for disclosure of operational risks, such as those studied by Brown et al. (2008), which do appear to be related to conflicts of interest or premature fund closure.

## References

- Abdulali, Adil, 2006, The bias ratio: Measuring the shape of fraud, *Protégé Partners Quarterly Letter*.
- Ackermann, Carl, Richard McEnally, and David Ravenscraft, 1999, The performance of hedge funds: Risk, return, and incentives, *Journal of Finance* 54, 833-874.
- Agarwal, V., N. Daniel, and N. Naik, 2007, Why is Santa so kind to hedge funds? The December return puzzle! Georgia State University Working Paper.
- Agarwal, V., and N. Naik, 2004, Risks and portfolio decisions involving hedge funds, *Review of Financial Studies* 17, 63-98.
- Ang, A., and N. Bollen, 2009, Locked up by a lockup: Valuing liquidity as a real option, Columbia University Working Paper.
- Asness, C., R. Krail, and J. Liew, 2001, Do Hedge Funds Hedge? *Journal of Portfolio Management* 28, 6-19.
- Beneish, M.D., 1999, The detection of earnings manipulation, *Financial Analysts Journal* 55, 24-36.
- Bollen, N., and V.K. Pool, 2008, Conditional return smoothing in the hedge fund industry, *Journal of Financial and Quantitative Analysis*, 267-298.
- Bollen, N., and V.K. Pool, 2009, Do hedge fund managers misreport returns? Evidence from the pooled distribution, *Journal of Finance*, forthcoming.
- Bollen, N., and R. Whaley, 2009, Hedge fund risk dynamics: Implications for performance appraisal, *Journal of Finance* 64, 987-1037.
- Brown, S., W. Goetzmann, and R. Ibbotson, 1999, Offshore hedge funds: Survival and performance, 1989–95, *Journal of Business* 72, 91-117.
- Brown, S., W. Goetzmann, and J. Park, 2001, Careers and Survival: Competition and Risk in the Hedge Fund and CTA Industry, *Journal of Finance* 56, 1869-1886.
- Brown, S., W. Goetzmann, B. Liang, and C. Schwarz, 2008, Mandatory disclosure and operational risk: Evidence from hedge fund registration, *Journal of Finance* 63, 2785-2815.
- Brown, S., W. Goetzmann, B. Liang, and C. Schwarz, 2009, Estimating operational risk for hedge funds: The  $\omega$ -score, *Financial Analysts Journal* 65, 43-53.
- Burgstahler, David and Ilia Dichev, 1997, Earnings management to avoid earnings decreases and losses, *Journal of Accounting and Economics* 24, 99-126.
- Carhart, Mark M., Ron Kaniel, David K. Musto, and Adam V. Reed, 2002, Leaning for the tape: Evidence of gaming behavior in equity mutual funds, *Journal of Finance* 57, 661-693.
- Devroye, Luc, 1997, Universal smoothing factor selection in density estimation, theory and practice, *Test* 6, 223-320.
- Ding, B., M. Getmansky, B. Liang, and R. Wermers, 2008, Investor flows and share restrictions in the hedge fund industry, SUNY Working Paper.
- Foster, F., T. Smith, and R. Whaley, 1997, Assessing goodness-of-fit of asset pricing models: The distribution of the maximal  $R^2$ , *Journal of Finance* 52, 591-607.
- Fung, W., and D. Hsieh, 1997, Empirical characteristics of dynamic trading strategies: The case of hedge funds, *Review of Financial Studies* 10, 275-302.

- Fung, W., and D. Hsieh, 2001, The risk in hedge fund strategies: Theory and evidence from trend followers, *Review of Financial Studies* 14, 313-341.
- Fung, W., and D. A. Hsieh, 2002, Asset-based style factors for hedge funds, *Financial Analysts Journal* 58, 16-27.
- Fung, W., and D. A. Hsieh, 2004, Hedge fund benchmarks: A risk based approach, *Financial Analysts Journal* 60, 65-80.
- Getmansky, M., A. W. Lo, and I. Makarov, 2004, An econometric model of serial correlation and illiquidity in hedge fund returns, *Journal of Financial Economics* 74, 529-609.
- Getmansky, M., A. W. Lo, and S. Mei, 2004, Sifting through the wreckage: Lessons from recent hedge-fund liquidations, *Journal of Investment Management* 2, 6-38.
- Goetzmann, W., J. Ingersoll, M. Spiegel, and S. Ross, 2003, High-water marks and hedge fund management contracts, *Journal of Finance* 58, 1685-1717.
- Goetzmann, W., J. Ingersoll, M. Spiegel, and I. Welch, 2007, Portfolio performance manipulation and manipulation-proof performance measures, *Review of Financial Studies* 20, 1503-1546.
- Greco, A., Malkiel, B. G., Saha, A., 2006, Why do hedge funds stop reporting their performance? CEPS working paper 124.
- Gregoriou, G., 2002. Hedge fund survival lifetimes, *Journal of Asset Management* 3, 237-252.
- Gregoriou, G., and F. Lhabitant, 2009, Madoff: A riot of red flags, *Journal of Wealth Management* 12, 89-98.
- Grove, H., and T. Cook, 2004, Lessons for auditors: Quantitative and qualitative red flags, *Journal of Forensic Accounting* 5, 131-146.
- Liang, B., 1999, On the performance of hedge funds, *Financial Analysts Journal* 55, 72-85.
- Liang, B., 2003, The accuracy of hedge fund returns, *Journal of Portfolio Management* 29, 111-122.
- Liang, B., and H. Park, 2008, Predicting hedge fund failure: A comparison of risk measures, *Journal of Financial and Quantitative Analysis*, forthcoming.
- Silverman, B. W., 1986. Density estimation for statistics and data analysis (Chapman and Hall, New York, NY.).
- Sirri, E. R., and P. Tufano, 1998, Costly search and mutual fund flows, *Journal of Finance*, 53, 1589-1622.
- Straumann, D., 2008, Measuring the quality of hedge fund data, *RiskMetrics Journal* Winter 2008, 65-93.
- Sun, Z., A. Wang, and L. Zheng, 2009, The road less traveled: Strategy distinctiveness and hedge fund performance, University of California, Irvine Working Paper.
- Titman, S., and C. Tiu, 2008, Do the best hedge funds hedge? University of Texas at Austin Working Paper.
- Waring, M., and L. Siegel, 2006, The myth of the absolute-return investor, *Financial Analysts Journal* 62, 14-21.
- Working, H., 1960, Note on the correlation of first differences of averages in a random chain, *Econometrica* 28, 916-918.

### Appendix. Variance for test statistic for discontinuity in distribution.

Define  $x_{i,j}$  as an indicator variable that equals one if observation  $i$  falls in bin  $j$  and zero otherwise. Let  $X_j$  denote the total number of observations that fall in bin  $j$ , i.e. for a sample size of  $n$  observations,

$$(A1) \quad X_j = \sum_{i=1}^n x_{i,j}, \quad x_{i,j} = \begin{cases} 1 & \text{if observation } i \text{ falls in bin } j \\ 0 & \text{otherwise} \end{cases}$$

Note that  $X_j$  and  $X_k$  are not independent since

$$(A2) \quad \begin{aligned} x_{i,j} = 1 &\rightarrow x_{i,k} = 0 \\ x_{i,k} = 1 &\rightarrow x_{i,j} = 0 \end{aligned}$$

The covariance between  $X_j$  and  $X_k$  is:

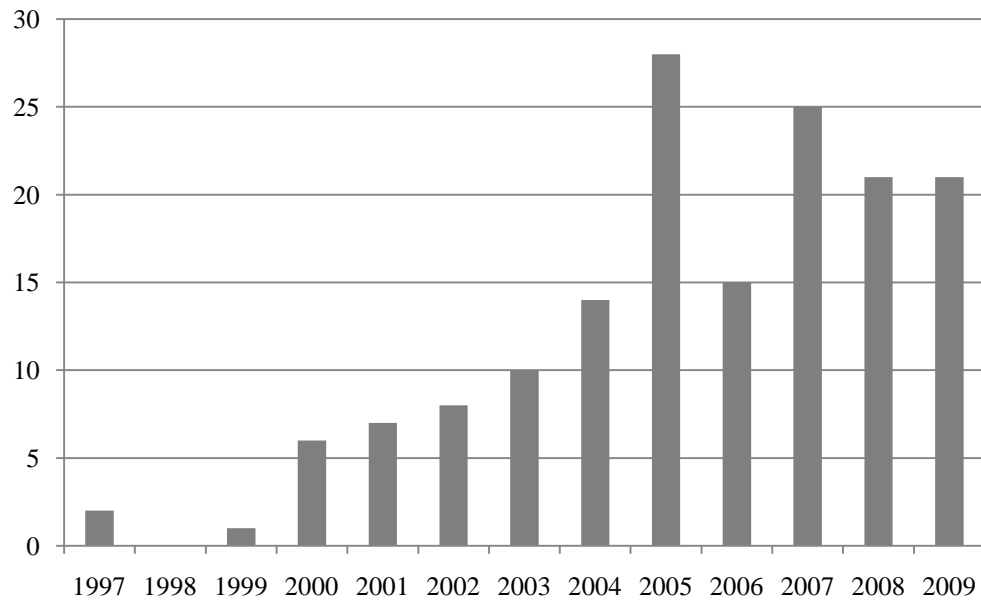
$$(A3) \quad \begin{aligned} Cov(X_j, X_k) &= E\left[(X_j - E[X_j])(X_k - E[X_k])\right] \\ &= E\left[\left(\sum_{i=1}^n (x_{i,j} - p_j)\right)\left(\sum_{i=1}^n (x_{i,k} - p_k)\right)\right] \\ &= E\left[\sum_{i=1}^n \left(\left(\sum_{i=1}^n (x_{i,j} - p_j)\right)(x_{i,k} - p_k)\right)\right] \\ &= E\left[\sum_{i=1}^n \left((x_{i,j} - p_j)(x_{i,k} - p_k)\right)\right] \\ &= E\left[\sum_{i=1}^n \left(-p_j x_{i,k} - p_k x_{i,j} + p_j p_k\right)\right] \\ &= -np_j p_k \end{aligned}$$

where the third line becomes the fourth line since there is assumed to be no time series relation between the observations. Our test compares the number of observations in a given bin (bin 2) and the average number of observations in the two immediately adjacent bins (bins 1 and 3). For this we need the variance of the difference:

$$(A4) \quad \begin{aligned} Var\left(X_2 - \frac{1}{2}(X_1 + X_3)\right) &= Var(X_2) + \frac{1}{4}Var(X_1) + \frac{1}{4}Var(X_3) - \\ &Cov(X_1, X_2) - Cov(X_2, X_3) + \frac{1}{2}Cov(X_1, X_3) \\ &= n(p_2 - p_2^2) + \frac{1}{4}n(p_1 - p_1^2 + p_3 - p_3^2) + np_2(p_1 + p_3) - \frac{1}{2}np_1 p_3 \end{aligned}$$

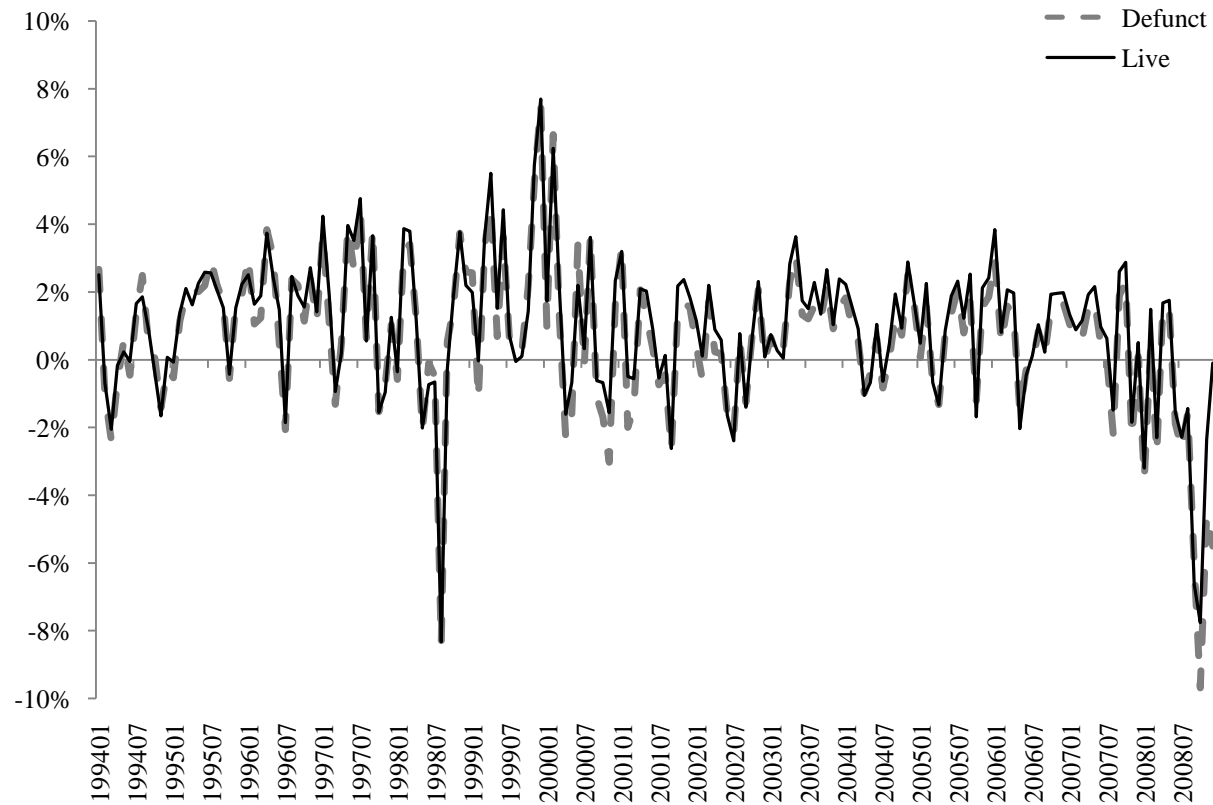
### Figure 1. Number of Enforcement Actions by Filing Year

Depicted is the number of SEC enforcement actions against hedge funds in our sample filed each year. The total number is 158.



## Figure 2. Live versus Defunct Fund Returns

Depicted is the cross-sectional average return of hedge funds in the CISDM and TASS databases. The average return is computed month-by-month over the period January 1994 through December 2008. The average return is computed for two subsets of the funds, defunct funds, which stopped reporting to the databases prior to the end of the database histories, and live funds, which continue to report returns to the end of the database histories.



**Table 1. Violation Types.**

“No. of Cases” is the number of SEC enforcement actions included in our analysis, categorized by the type of alleged violation committed. A total of 158 enforcement actions with filing dates between 6/18/1997 and 6/4/2009 were collected from the SEC’s website. “No. of SEC Funds” is the number of funds in our hedge fund return sample associated with each enforcement action categorized by the type of alleged violation. A total of 93 funds are in our sample. Some of the actions and funds involve more than one type of violation.

Violation	No. of Cases	No. of SEC Funds
Misappropriation	45	14
Overvaluation	55	32
Misrepresent	52	19
Ponzi	13	2
Short Sale Violation	17	30
Insider Trading	11	5
Other	35	22
<i>Total</i>	228	124

**Table 2. Hedge Fund Styles.**

Listed are the names of 13 hedge fund styles describing the strategies of the hedge funds in our sample. The list is a combination of the categories used in the TASS and CISDM hedge fund databases. Also listed, by style, is the number of hedge funds included in our sample, labeled “All Funds,” as well as the number of hedge funds in our sample that are the subject of SEC enforcement actions, labeled “SEC Funds.”

Style	All Funds	SEC Funds
Equity Long/Short	3,856	44
Multi-Strategy	889	18
Event Driven	761	3
Emerging Markets	680	0
Equity Market Neutral	610	3
Fixed Income Arbitrage	573	8
Global Macro	536	6
Convertible Arbitrage	334	5
Sector	213	3
Other	109	3
Distressed Securities	90	0
Single Strategy	60	0
Short Bias	59	0
<i>Total</i>	8,770	93

**Table 3. Summary Statistics.**

Listed are summary statistics of hedge funds in our sample. The summary statistics are the equally-weighted cross-sectional averages of the mean monthly return,  $\mu$ ; the standard deviation of monthly returns,  $\sigma$ ; the Sharpe ratio,  $SR$ ; the skewness,  $Skew$ ; the excess kurtosis,  $Kurt$ ; the first-order serial correlation coefficient,  $AR(1)$ ; and the percentage of funds with a positive and statistically significant first-order serial correlation coefficient,  $\% >> 0$ . Results are split by whether the funds are Live or Defunct, and are also displayed for both together. Panel A shows results for the subsample of funds that are the subject of SEC enforcement actions, labeled “SEC Funds.” Panel B shows the results for all other funds. Below each statistic is the  $p$ -value from a test that the corresponding statistics in Panel A and B are the same. Panel C shows the results for a control group of funds, as well as  $p$ -values testing for a difference between the results in Panel A and Panel C. For each SEC fund, 10 other funds are selected as controls. These 10 are in the same style as the SEC fund, with the same Live/Defunct status, and with beginning and ending dates in the database within 24 months of the SEC fund. Return data are from the CISDM and TASS databases.

Type	No. of funds	$\mu$	$\sigma$	$SR$	$Skew$	$Kurt$	$AR(1)$	$\% >> 0$
Panel A. SEC Funds								
Live	28	0.0088	0.0313	0.2303	0.3872	5.8072	0.1999	0.5357
Defunct	65	0.0124	0.0398	0.3499	-0.8008	10.6689	0.1407	0.2308
All	93	0.0113	0.0372	0.3139	-0.4431	9.2052	0.1585	0.3226
Panel B. All Other Funds								
Live	3,992	0.0052	0.0398	0.0972	-0.6630	5.1365	0.2159	0.4481
<i>p-value</i>		0.0036	0.0068	0.0007	0.0057	0.7816	0.6816	0.0633
Defunct	4,685	0.0073	0.0419	0.1785	-0.2158	4.1507	0.1435	0.2564
<i>p-value</i>		0.0000	0.5770	0.0002	0.0961	0.0138	0.9358	0.3479
All	8,677	0.0064	0.0409	0.1411	-0.4215	4.6042	0.1768	0.3446
<i>p-value</i>		0.0000	0.1938	0.0000	0.9362	0.0201	0.4957	0.3742
Panel C. Control Group Funds								
Live	139	0.0052	0.0322	0.0637	-0.3456	4.8334	0.2319	0.5180
<i>p-value</i>		0.0048	0.7863	0.0001	0.0588	0.6984	0.4337	0.7319
Defunct	491	0.0083	0.0540	0.1518	-0.2033	3.9967	0.1694	0.2892
<i>p-value</i>		0.0012	0.0014	0.0000	0.0941	0.0123	0.4204	0.0492
All	630	0.0076	0.0492	0.1323	-0.2347	4.1813	0.1832	0.3397
<i>p-value</i>		0.0002	0.0004	0.0000	0.4505	0.0121	0.3753	0.5149

#### Table 4. Flag Frequencies.

Listed is the percentage of hedge funds that trigger each quantitative flag. Results are shown for 93 funds associated with SEC enforcement actions (SEC Funds), the other 8,693 funds in our sample (All Other Funds), and a control group of 630 funds (Control Group Funds). The control group is constructed by matching each SEC fund with 10 other funds by strategy, correlation, and live/defunct status. “%Zero” tests for an unusually high number of returns exactly equal to zero. “%Unique” tests for an unusually high number of returns that are repeated. “Uniform” tests for a distribution of last digit that is significantly different from a uniform distribution. “String” tests for an unusually long string of repeated returns. “Pairs” tests for an unusually high number of pairs of repeated returns. “AR(1)” tests for a statistically significant and positive first-order serial correlation coefficient. “CAR(1)” tests for a statistically significant larger serial correlation conditioned on a negative lagged fitted value from a regression involving an optimal set of style factors. “*maxrsq*” tests for an adjusted R-squared significantly different from zero at the 90% level. “*kink*” tests for a discontinuity at zero in the distribution of a hedge fund’s returns.

Flag	SEC	All Other	<i>p</i> -value	Control	<i>p</i> -value
	Funds ( <i>N</i> = 93)	Funds ( <i>N</i> = 8,693)		Group Funds ( <i>N</i> = 630)	
%Zero	9.7%	16.1%	0.0951	11.4%	0.6172
%Unique	24.7%	24.8%	0.9794	17.8%	0.1082
Uniform	31.2%	37.7%	0.1971	29.5%	0.7439
String	17.2%	21.0%	0.3659	14.9%	0.5671
Pairs	2.2%	8.3%	0.0317	5.7%	0.1505
AR(1)	32.3%	34.5%	0.6568	34.0%	0.7447
CAR(1)	5.4%	4.6%	0.7133	4.4%	0.6877
<i>maxrsq</i>	24.7%	27.3%	0.5864	13.2%	0.0033
<i>kink</i>	22.6%	17.4%	0.1885	14.6%	0.0480

**Table 5. Maximum  $R^2$ .**

Listed are summary statistics of the maximum  $R^2$  from regressions of hedge fund returns on a standard set of style factors. The maximum  $R^2$  is obtained by searching over subsets of at most 3 factors from the complete set of 14 factors. The factors include the market excess return, the Fama-French size and value factors, the momentum factor, the squares of the size, value, and momentum factors, the five Fung and Hsieh trend-following style factors, the change in the 10-year Treasury yield, and the change in the credit spread. Results are shown for all 8,770 funds in the CISDM and TASS datasets in our sample. Results are listed separately on categories formed by the number of years of data available that overlaps with the factor returns, where  $n$  years indicates between  $12n$  and  $12n+11$  months. Listed are: the number of funds (“No. of Funds”), the number of funds for which we fail to reject the hypothesis that the adjusted  $R^2$  is zero (“No. of Flags”), the average maximum adjusted  $R^2$  obtained (“Avg.  $R^2$ ”), and the average fund-specific 90<sup>th</sup> percentile critical value for the adjusted  $R^2$  (“90<sup>th</sup> %”).

Years	No. of Funds	No. of Flags	Avg. $R^2$	90 <sup>th</sup> %
2	1,910	759	42.6%	36.6%
3	1,595	449	40.0%	26.2%
4	1,226	286	36.2%	20.2%
5	960	176	34.9%	16.6%
6	798	116	34.1%	13.9%
7	545	75	30.9%	12.1%
8	422	60	31.7%	10.6%
9	317	37	32.2%	9.4%
10	212	29	28.0%	8.5%
11	229	27	31.0%	7.7%
12	183	13	28.7%	7.1%
13	142	8	33.7%	6.7%
14	231	5	33.4%	6.1%

**Table 6. Flow-performance Sensitivity.**

Listed are the results of regressions of annual fund flow, as a percentage of beginning of year assets under management, on lagged performance. Performance measures are based on percentiles of raw returns relative to all other funds in a fund's style category, and are split by quartile, as defined as follows for fund  $i$  in year  $t-1$ :

$$qrnk4_{i,t-1} = percentile_{i,t-1} - 0.50 \text{ if } 0.00 \leq percentile_{i,t-1} < 0.25 \text{ and } 0 \text{ otherwise}$$

$$qrnk3_{i,t-1} = percentile_{i,t-1} - 0.50 \text{ if } 0.25 \leq percentile_{i,t-1} < 0.50 \text{ and } 0 \text{ otherwise}$$

$$qrnk2_{i,t-1} = percentile_{i,t-1} - 0.50 \text{ if } 0.50 \leq percentile_{i,t-1} < 0.75 \text{ and } 0 \text{ otherwise}$$

$$qrnk1_{i,t-1} = percentile_{i,t-1} - 0.50 \text{ if } 0.75 \leq percentile_{i,t-1} \leq 1.00 \text{ and } 0 \text{ otherwise}$$

Interactions terms, denoted by  $X_j$ , are the product of  $qrnkj$  and an indicator variable that equals one if a fund is in the SEC subsample and zero otherwise. Other variables are defined as follows: "cat\_flow" is the contemporaneous average percentage flow to funds in the same style category, "ln(size)" is the lagged log of fund assets, "vol" is the lagged return volatility, "mgtfee" is the fixed management fee, and "incentive" is the fund's performance bonus.

Variable	Model 1			Model 2		
	Estimate	Std Error	<i>p</i> -value	Estimate	Std Error	<i>p</i> -value
Intercept	0.0542	1.9828	0.9787	0.0473	1.9739	0.9813
cat_flow	-0.2303	0.1413	0.1316	-0.2325	0.1404	0.1259
size	0.9150	0.1471	0.0000	0.9248	0.1489	0.0000
vol	-2.8105	0.7201	0.0025	-2.8238	0.7343	0.0027
mgtfee	0.1563	0.0698	0.0468	0.1573	0.0691	0.0438
incentive	0.0057	0.0052	0.2963	0.0059	0.0051	0.2768
<i>qrnk1</i>	2.1267	0.2265	0.0000	2.1318	0.2319	0.0000
<i>qrnk2</i>	3.0902	0.5055	0.0000	3.0841	0.5100	0.0000
<i>qrnk3</i>	0.3363	0.2775	0.2509	0.3230	0.2740	0.2633
<i>qrnk4</i>	0.5910	0.0767	0.0000	0.5842	0.0766	0.0000
$X_1$				-0.5901	0.5354	0.2939
$X_2$				-1.9766	5.7222	0.7363
$X_3$				1.1179	0.4763	0.0387
$X_4$				0.7849	0.1980	0.0022
Adj. <i>R</i> -squared	4.2%			4.0%		