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# Essays on Hedge Funds Performance: Dynamic Risk Exposures, Anomalies, and Unreported Actions

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# ESSAYS ON HEDGE FUND PERFORMANCE: DYNAMIC RISK EXPOSURES, ANOMALIES, AND UNREPORTED ACTIONS

A Dissertation Presented

by

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# ABSTRACT

## ESSAYS ON HEDGE FUND PERFORMANCE: DYNAMIC RISK EXPOSURES, ANOMALIES, AND UNREPORTED ACTIONS

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The first essay analyzes hedge fund activeness and its impact on hedge fund performance. We propose an innovative method to estimate time-varying risk exposures of hedge funds. The activeness is measured as the time-series average of sum of changes in risk exposures. We examine cross-section and time-series variation of activeness among hedge funds. The activeness can be explained by fund characteristics such as age, lockup period, performance fee, and past performance. Using four performance measures, we find little evidence of active funds outperforming others over the sample period 1994 through 2013. We find that activeness tend to yield better performance only in the pre-2002 period and such effect exists mainly for fund strategies that make directional bets.

The second essay studies how hedge funds' activities in exploiting stock anomalies impact fund performance. Using a sample of 3024 equity-oriented hedge funds and 10 stock anomalies, we find that hedge funds overall trade on the correct side of the anomalies.

The decile 10 portfolio of hedge funds that trade on stock anomalies most intensively outperform the decile 1 portfolio of hedge funds by 2.16% of Fama-French (1993) alpha per annum and by 0.17 in appraisal ratio per annum. We find that crowdedness of hedge funds exploiting stock anomalies and competition among hedge funds weakens the effectiveness of exploiting stock anomalies in generating risk-adjusted performance.

In the third essay, we study the importance of unique stock holdings and unreported actions as the source of hedge fund performance. We calculate four holdings-based uniqueness measures. We find that these holdings-based uniqueness measures are not associated with fund alpha and appraisal ratio. The unreported actions, on the contrary, positively predict hedge fund performance. We also find that hedge funds with greater level of unreported actions tend to exhibit less risk and greater return gap.

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# CHAPTER 1

# HEDGE FUND ACTIVENESS AND PERFORMANCE

## 1.1 Introduction

In this chapter we study hedge funds' trading activities based on factor exposures, which we term "activeness", and their impact on hedge fund performance. In the last two decades, the hedge fund industry has seen a tremendous growth in asset under management, from \$118 billion in year 1997 to \$2.2 trillion as of year 2013.[1] Hedge funds charge investors management and incentive fees to reward their active management, typically with a fee structure of "2/20". Due to the increasing popularity of investment in hedge funds and the incentive structure for hedge fund managers, the question of whether hedge fund managers have commensurate skills has gained wide interests among practitioners as well as academics. After all, compared with their mutual fund peers, hedge funds are less restricted in implementing the investments. Therefore, hedge fund managers enjoy greater flexibility, and thus are expected to be able to dynamically adjust investment positions as needed, potentially in a way that a traditional active manager may not. For example, if both a hedge fund manager and a mutual fund manager predict a negative return from a factor exposure, the hedge fund manager can change her positions to take a negative exposure to that factor while the mutual fund managers may be refrained from doing so.

Given such advantage of hedge funds, one would be interested in whether hedge funds indeed exhibit time-varying risk exposure. This question has been addressed in recent liter-

[1] Data is from `http://www.barclayhedge.com/`.

ature[2]. One would thus further ask whether hedge funds' actively adjusting their investment positions according to their information and judgment can create value for the investors. Also, what types of hedge funds and under what circumstances tend to be more active? Thus, the properties of hedge funds activeness and its impact on hedge fund performance are the main interest of this chapter.

Ideally, we could accomplish this analysis if she has access to details of holdings for hedge funds in each period. However, hedge funds are quite protective of information regarding their investments and the information disclosed is very limited. Therefore, it is hard to study hedge funds' activeness by analyzing their investment positions directly[3]. We take an alternative path. With a multi-factor model, we estimate time-varying fund exposures to risk factors, which become the basis for our subsequent analysis.

We use a large set of factors, covering stocks, bonds, commodities, and currencies, to analyze the risks and returns of hedge funds. Hedge funds may have non-linear exposures to risk factors. To alleviate the potential bias because of omitted factors, we include Fung and Hsieh (2004) [43] trend-following factors for robustness checks. When estimating time-varying risk exposures, unlike prior research, we adopt an innovative method of estimating time-varying hedge fund risk exposures. Specifically, we first estimate time-varying variance-covariance matrix for hedge fund monthly returns and risk factors using dynamic conditional correlation approach suggested by Engle (2002) [33]. In order to obtain a parsimonious model for hedge fund returns, for each variance-covariance matrix, we apply a statistical method based on Bayesian Information Criterion (BIC) to get a subset of risk factors that are important for the fund at each time period. Then we can estimate the exposures to the relevant factors and obtain dynamic conditional betas Engle (2012) [34].

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[2]The literature on this issue includes Billio et al. (2012)[19], Bollen and Whaley (2009)[22], Fung et al. (2008)[44], and Patton and Radomorai (2013)[69], among others.

[3]Griffin and Xu (2009) [51] examine hedge fund long-equity holdings and find no evidence of timing abilities among hedge funds. We are interested in the broad hedge fund industry, not just limited to the equity hedge funds.

Our way of estimating changing hedge fund risk exposures and identifying relevant risk factors differs from previous research in that our GARCH-based method not only avoids specifying rolling window widths but also conducts variable selection dynamically, which is consistent with the fact that hedge funds have the flexibility of switching asset classes as well as changing positions.

With the estimated time-varying loadings on systematic factors, we propose a measure of hedge fund activeness, which is defined as the sum of absolute value of monthly changes in risk factor exposures, averaged in a certain period. This measure appears similar to turnover of hedge funds, but we emphasize that it measures how actively hedge funds manage their risk exposures. We first analyze the cross-section and time-series properties of hedge fund activeness defined in our way. We then examine the determinants of hedge fund activeness and whether hedge fund activeness pays off, i.e., whether such activities lead to better performance. Our results are based on a sample of 8,011 hedge funds obtained from the CISDM database and the TASS database.

The main results of this paper are summarized as follows. We show significant cross-section differences in activeness within and across hedge fund investment styles. Directional traders are the most active of the six broad hedge fund styles. Hedge funds act differently under different market conditions. We find that the two peaks of hedge fund activeness over our sample period coincide with the technology bubble and the 2008 financial crisis. The finding that hedge funds appear abnormally active in 2008 is consistent with the findings of Ben-David et al. (2012) [17]. Moreover, hedge fund activeness displays persistence—funds that are active in the past tend to continue to be active in the subsequent periods.

Regarding the determinants of hedge fund activeness, we find that fund size is negatively associated with hedge fund activeness. Also, hedge funds that experience higher inflows tend to be less active. The age of funds is negatively related to hedge fund activeness as older funds have established their reputation and do not need to be as aggressive and active as younger funds. Funds with longer lockup periods tend to be more active because they have more freedom. We also find that performance fee gives hedge funds incentives to manage their risk exposures more actively. In addition to these fund characteristics, we find that past performance of hedge funds has a dampening effect on subsequent level hedge fund activeness. Interestingly, the interaction between past performance, both cumulative returns and the rank of cumulative returns among hedge fund peers, and performance fee has a significantly negative coefficient, suggesting that hedge funds that have achieved good performance concern about the performance fee they can get and tend to be less active subsequently.

We then use four performance metrics to study the impact of hedge fund activeness on performance, namely, the alpha, the appraisal ratio, the Sharpe ratio, and the manipulation-proof performance measure (MPPM). We employ portfolio sorting analysis as well as the multivariate regression analysis. The sorting approach shows that the evidence of hedge fund activeness yielding better performance is mixed–funds that are more active tend to have higher alpha but the other three performance measures tend to be lower. We then conduct multivariate regressions, controlling for the variables that may potentially influence hedge fund performance. At the whole industry level, the multivariate regression shows that there is little evidence of relation between hedge fund performance and activeness during our full sample period. We find that hedge fund activeness produces higher alpha and appraisal ratio only in the period prior to 2002. The results remain qualitatively unchanged when we include Fung and Hsieh (2004) [43] trend-following risk factors, and when we use an alternative measure of hedge fund activeness. The insignificant relation between fund activeness and performance in the post-2002 period is not because of the difficult times during the financial crisis. When the 2008 financial crisis period is excluded, we actually find a significantly negative relation between hedge fund activeness and performance using both the Fama-MacBeth (1973) [35] regression and the panel regression. Consistent with the findings of Griffin and Xu (2009) [51], hedge funds' intense trading activities barely yield better performance. Style breakdown analysis shows that the impact of activeness on fund performance in the pre-2002 period mainly exists in the Directional Traders hedge fund style.

This paper makes several contributions to the literature. First, this paper contributes to the literature studying the dynamics of hedge fund risk exposures by introducing an innovative way to dynamically select risk factors for hedge funds as well as to estimate the time-varying factor loadings. This approach is consistent with the fact that hedge funds are able to invest in various asset classes and switch positions as needed. Moreover, in contrast to rolling least square regressions which estimate average risk exposures of hedge funds within a certain time window, our method is able to capture the risk exposures as well as their changes month by month. Second, we conduct comprehensive study of properties of, and determinants of hedge fund activeness in trading and managing risk exposures. This is important as it helps us understand the trading activities of hedge funds. Third, our paper adds to the literature on hedge fund performance by studying whether hedge fund activeness is able to yield better performance. With better understanding of hedge funds' trading activities and the outcomes investors can make sensible decisions pertaining to investing in hedge funds.

The rest of the chapter is organized as follows. Section 2 explains the model and the estimation method for hedge fund risk exposures. Section 3 describes the data we use. Section 4 presents the main empirical results of this paper. We conduct robustness checks in Section 5 and conclude in Section 6. The results of simulation are shown in the Appendix.

## 1.2 Model and Methodology

The linear factor model has been widely applied in the asset pricing literature and is the foundation of the analysis in this article. Assume that hedge fund $i$'s returns can be written, using a linear factor model, as

$$R_{it} = \alpha_i + \sum_{j=1}^{K} \beta_{ijt} F_{jt} + \epsilon_t, \tag{1.1}$$

where $\beta_{ij}$ is the hedge fund $i$'s exposure to systematic factor $F_j$ and the dynamic property of hedge fund risk exposures is captured by the subscript $t$ of the $\beta' s$.

If a hedge fund manager sensibly change her exposures to systematic factors, such decisions should be based on her best knowledge and information. In other words, the risk exposure $\beta$ at time $t$ should be a function of information up to time $t-1$, $I_{t-1}$, that the hedge fund manager has, i.e., $\beta(I_{t-1})$. The information can be public and/or private. We do not assume any form, e.g. linear, for the function that determines the evolution of $\beta_t$.

### 1.2.1 Risk Factors

One appeal of investing in hedge funds is that hedge funds can produce option-like pattern of returns that are particularly useful for reducing risks especially in poor states of economy. However, it has been shown that hedge funds are exposed to systematic risk. There is a large body of literature on identifying risk factors that can be used to facilitate understanding hedge fund risk and returns.

Fung and Hsieh (1997) [39] extend Sharpe (1992) [71] style factor model and include additional factors resulting from principal component analysis to analyze hedge fund returns. These statistical factors are difficult to be linked to economic variables. Fung and Hsieh (2002) [42] then advocate asset-based style factors because they have the advantage of transparency and investability. Researchers thus have constructed factors that exhibit option-like payoff features to capture the common risk factors in hedge funds (See, for example, Fung and Hsieh (2001) [41], Fung and Hsieh (2004) [43], and Agarwal and Naveen (2004) [2]). Despite the fact that hedge funds can trade derivatives, most hedge funds employ many of the same asset classes as traditional investment vehicles. Liang (1999) [62] considers eight asset-class factors, and Fung and Hsieh (2002) [42] consider nine. Recently, there is a growing literature of using liquid assets to replicate hedge fund returns (see Hasanhodzic and Lo (2007) [53], Amenc et al. (2010) [8], and, Bollen and Fisher (2012) [21]).

In our baseline analysis, we consider a large set of factors that cover a wide range of markets and credit quality as hedge funds can invest in a large variety of assets. For equities, we include returns of the S&P 500, the MSCI World ex US index, the MSCI Emerging Markets Investable Market Index, the momentum factor, as well as the returns spread between the Russell 2000 and Russell 1000 indexes, and that of Russell 1000 Value versus Growth indexes; for bonds, the Barclays Aggregate Bond Index, the J.P. Morgan Emerging Markets Bond Global Index, the CITI World Government Bond Index, the Barclays High Yield Index, and the change in the spread of 10-year Treasury bond yield and 3-month Treasury bill yield; for commodities, the S&P GSCI Total Return and the S&P GSCI Gold Total Return; for currency, , the U.S. Federal Reserve Bank trade-weighted dollar index; for credit, the change in default spread measured as the the Moody's Baa corporate bond yields less those of Aaa bonds.

Brandon and Wang (2013) [23] show that liquidity risk is a source of hedge fund returns. Cao et al. (2013) [28] show that hedge funds can time market liquidity. Thus we include the Pastor and Stambaugh (2003) [68] liquidity factor in our set of factors.

### 1.2.2 Dynamic Variable Selection and Estimation of Risk Exposures

In order to capture the systematic factors that hedge funds load on, taking into account the fact that hedge funds can invest in different types of asset classes, we have proposed a number of factors following the extant literature. However, because the number of factors is relatively large compared to the number of observations for typical hedge funds and because hedge funds usually have concentrated portfolios, we need to identify a subset of factors for hedge funds.

We desire to obtain time-varying risk exposures for hedge funds to examine the relation between activeness and performance. There are several methods for estimating time-varying coefficients, among which the rolling ordinary least squares is particularly popular. This method selects a estimation window (for example, 24 months) and roll forward to conduct OLS in each regression window. Each time the information contained in the observations in the regression window is used while older information is discarded. However, it's unclear under what assumptions this method yields consistent conditional estimators. Estimates thus might be sensitive to the width of the regression window.

Prior literature on hedge fund risks and returns either use a fixed number of risk factors or select a few factors from a large number of factors but use those factors for the entire history of the hedge funds. For example, Agarwal and Naveen (2004) [2], Liang (1999) [62], and, Titman and Tiu (2011) [75] apply the stepwise regression to select factors; Bollen and Whaley (2009) [22], and Jaganathan et al. (2010) [55] select a small number of risk factors based on the Bayesian Information Criterion. These methods are static. Considering the highly dynamic feature of hedge funds in both asset classes and positions, we believe that it is plausible to dynamically select factors for hedge funds and estimate the corresponding exposures to those factors.[4] In this way, we can account for both switches in different risk factors and changes of exposures in the same factors. Our approach is based on the work of Engle (2002) [33] and Engle (2012) [34]. Specifically, we first estimate a dynamic conditional correlation model and obtain a time series of variance-covariance matrices for each fund. This is done in two steps as suggested by Engle (2002). Each return series is assumed to be and estimated as a GARCH(1,1) process to obtain conditional variances $\sigma_t^2$. Next, the conditional correlation $\rho_{ijt}$ between return series $i$ and $j$ is estimated based on the mean-reverting dynamic conditional correlation model. The conditional covariance $\sigma_{ijt} = \rho_{ijt}\sigma_{it}\sigma_{jt}$ is the corresponding element in the conditional covariance matrix $H_t$. Then we use these variance-covariance matrices to select a subset of risk factors based on the BIC for each month. After identifying the risk factors for a fund in a certain month,

[4]McGuire and Tsatsaronis (2008) [64] select factors on a rolling basis. But this method is subject to the flaws of rolling regression discussed earlier.

with the variance-covariance matrix for that month, we can compute the factor exposures for the identified factors as

$$\beta_t = \Sigma_{FF,t}^{-1}\Sigma_{FR,t} \tag{1.2}$$

where $\Sigma_{FF,t}$ is the covariance matrix for identified factors at $t$, and $\Sigma_{FR,t}$ is the covariance matrix for identified factors and hedge fund returns. The loadings for other factors in month $t$ equal 0.

The variation of hedge funds' risk exposures may result from the changes of hedge funds' positions and/or asset classes invested in. Even if the hedge fund chooses not to make any changes regarding its investment positions, the change in risk exposures of the hedge fund is a decision made by the hedge fund, thus a result of active management. Hedge fund managers manage the capital on behalf of investors and charge investors relatively high fees, so it is important to understand whether fund managers' activeness yields better payoffs for investors. [69] compare the static model and the time-varying beta model, and conclude that changing factor loadings, on average, results in higher risk-adjusted returns. Their focus is on the importance of accounting for time-varying risk exposures when evaluating hedge fund performance. We attempt to address the question whether funds that are more active in adjusting their risk exposures tend to perform better. We propose a simple measure to proxy the activeness (ACT) of hedge funds which is defined as the sum of absolute value of changes in risk factor exposures, averaged in a certain period.

$$ACT_i = \frac{1}{T}\sum_{t=1}^{T}\sum_{k=1}^{K}|\beta_{ikt} - \beta_{ikt-1}| \tag{1.3}$$

We employ two approaches–the portfolio sorting approach and the regression approach–to study the relation between hedge fund performance and trade activeness. Specifically, for the portfolio approach, in each month, we sort the hedge funds into quintiles based on the proxy measure for trade activeness. We compute the average performance measures for each quintile group. Then we test the difference of performance measures of the top and the bottom quintiles. Though straightforward, this approach does not control for other variables that are related to fund performance. We then use the widely-used Fama and MacBeth (1973) [35] method to analyze this problem, controlling for a number of hedge fund characteristics. It is well known that Fama-MacBeth regression calculates standard errors by correcting for the time effect, so we also conduct panel data regression and control for the fund effect in case there is.

## 1.3 Data

The hedge fund data comes from the CISDM database and the TASS database. The sample period spans from January 1994 to December 2013. The dataset originally contains a total of 41,146 hedge funds, including both live funds and defunct funds as of December 2013. Many hedge funds in the dataset often have several classes of shares and these share classes have almost identical (or at least highly correlated) returns. Funds denoted in a currency other than the US dollars are deleted. This procedure leaves us with 24,250 hedge funds. We remove those duplicates from our sample as in Aggarwal and Jorion (2010) [5]. This procedure yields 20,325 hedge funds. It is well known that hedge funds often report returns of incubation period to the hedge fund data vendors thus creating a backfill bias (See, for example, Fung and Hsieh (2000) [40]). Following convention in the literature, we delete the first 12 return observations for each fund considering the short history of hedge funds. We require that each hedge fund in our sample have at least 36 non-missing return observations to obtain meaningful estimates of factor exposures. This essentially requires a fund to have a history of at least 4 years of observations in order to be included in our sample. We are left with 10,877 hedge funds. Finally, we also apply a filter that the asset under management (AUM) must exceed 10 million US dollars some time over the life of the hedge fund. After applying these data requirements, our final sample consists of a total of 8011 hedge funds. To mitigate the survivorship bias, we include both live funds and defunct funds in our analysis. Still, we acknowledge that our filters applied may result in survivorship bias.

The sample hedge funds are consolidated into 6 categories–namely, directional traders, security selection, relative value, funds of funds, multi-process, and others– according to the Morningstar category classifications for hedge funds[5] and Agarwal et al. (2009) [3].

Table 1 provides summary statistics for some characteristics of hedge funds in our sample. Panel A and Panel B present some fund characteristics for live funds and defunct funds, respectively. The average age (defined as number of observations divided by 12) of live funds in our sample is 11.07 years, while that of the defunct funds is 8.36 years. Column 2 reports the most recent size in $M (asset under management). Live funds are generally larger than defunct funds. The average size of live funds is 217.48 $M while that of defunct funds is 155.23 $M, and other percentiles indicate that live hedge funds tend to have greater AUM. Slightly than half (47%) of the live funds in our sample are offshore funds and the number is 53% for defunct funds. Hedge funds often stipulate a lockup period and a notice period of redemption so that they can fully implement their investment ideas. The summary statistics show that there is not much difference in these two variables between live funds and defunct funds. The average lockup period and redemption notice period for live funds are slightly longer than those of defunct funds. The management fee charged by hedge funds typically range from 0 to 3% and the performance fee between 10% and 30%. The average performance fee charged by live funds is just slightly less than that by defunct funds. High water mark is the highest value that an investment fund has reached for investors. Since hedge funds often charge performance-based fees, high water mark ensures that hedge fund managers do not charge large amount of fees for poor performance. HW is a dummy variable with 1 denoting high water mark is utilized. Table 1

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[5] See `https://corporate.morningstar.com/us/documents/MethodologyDocuments/MethodologyPapers/MorningstarHedgeFundCategories_Methodology.pdf` which is effective April 2012. Funds of hedge funds are grouped into a separate category.

shows that 78% of live hedge funds and 71% of defunct funds utilize high water mark. The last column reports the usage of leverage among hedge funds. It appears that live funds and defunct funds have almost the same portion of funds that utilize leverage.[6]

Panel C of Table 1 (excluding the last row) contains summary statistics (in units of percentage) of the de-smoothed returns for all funds, as well as for subsets of hedge funds. Our sample covers the 2008 financial crisis, thus the average monthly return, 0.74% is lower than that reported by prior research (e.g., Bollen and Whaley (2009) [22]). Also, because of the turmoil of the financial crisis, the monthly return volatility is higher. Directional trader funds have the highest mean return, 0.89%, and highest standard deviation, 7.39%, while funds of funds' mean return is the lowest, only 0.50%, with the lowest standard deviation of 3.95% among all strategies. The low returns of funds of hedge funds may result from the additional fees charged by these funds. But it appears that they provide some benefits of diversification. The next three rows provide the means of hedge funds' Sharpe Ratio, skewness and excess kurtosis[7], respectively. The mean Sharpe ratio for all sample funds is 0.2175 and directional traders have a significantly lower mean Sharpe ratio, 0.1722, compared with other fund styles. Finally, hedge fund returns are generally skewed to the left except two styles–Directional Traders and Security Selection, and they all exhibit substantial excess kurtosis, which indicates a thick-tail feature for hedge fund return distributions.

Hedge fund returns are usually smoothed as suggested by Getmansky et al. (2004) [45], evidenced by the significant serial correlation in hedge fund returns which would depress hedge fund return volatility and inflate the Sharpe ratio. The first-order autocorrelation values are obtained by estimating an AR(1) model for hedge fund monthly reported returns.

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[6]However, we acknowledge that there is a significant portion of missing values for some of these fund characteristics in our sample, especially for whether hedge funds adopt leverage.

[7]Following [22], skewness is computed as $\frac{n}{(n-1)(n-2)s^3}\sum_{t=1}^{n}(r_t-\bar{r})^3$, and excess kurtosis is computed as $\frac{n(n+1)}{(n-1)(n-2)(n-3)s^4\sum_{t=1}^{n}(r_t-\bar{r})^4} - 3\frac{(n-1)^2}{(n-2)(n-3)}$, where $s$ is the standard deviation.

The mean value of first order autocorrelation of the raw returns across all funds in our hedge fund sample is 0.1981 as shown in the last row of Panel C in Table 1. Across fund styles, funds of hedge funds exhibit the highest level of AR(1) coefficient. Bollen and Whaley (2009) [22] discuss three possible reasons for this fact. On the other end, the funds in the Directional Traders group exhibit the lowest average AR(1) coefficient. This can be attributed to the fact that funds in this group, especially managed futures funds mainly count on highly liquid assets. Asness et al. (2001) [12] show that simple beta estimates without accounting for the autocorrelation in returns would underestimate hedge fund risk exposures. They suggest using lagged factors to correct for this issue. Since hedge funds generally have a relatively short history, we opt to correct for the autocorrelation in the hedge fund returns. In this paper, we apply a simple formula as follows to each hedge fund in our sample to obtain smoothing-adjusted hedge fund returns

$$r_{it} = \frac{R_{it} - \rho R_{it-1}}{1 - \rho} \tag{1.4}$$

where $r_{it}$ is the de-smoothed return for hedge fund $i$ in month $t$ and $R_{it}$ is the corresponding raw return. $\rho$ is the first-order autocorrelation for returns of fund $i$. The subsequent estimates of fund factor exposures are based on the smoothing-adjusted returns.

## 1.4 Empirical Results

### 1.4.1 Properties of Hedge Fund Activeness

We first examine the properties of hedge fund activeness. For individual hedge funds, the measure of hedge fund activeness is computed based on the methodology discussed in Section 2. Thus, each hedge fund has a time series of monthly activeness measures. We then take time-series average of monthly changes in risk exposures for each hedge fund and calculate the cross-sectional average activeness across funds within a hedge fund investment style. Table 2 presents summary statistics of activeness for each hedge fund style.

We observe notable cross-sectional variation of activeness within each hedge fund group. Of the six hedge fund styles, directional traders tend to be the most active ones. The mean activeness of directional traders is 0.8085 which is the highest. Conventional percentiles (25th Percentile, median, and 75th percentile) also indicate that directional traders tend to be more active than other styles. This is consistent with our expectation as these funds often make directional bets. Another interesting observation is that managed futures funds which are known to be very active in trading are identified to be very active by our method. Specifically, the mean activeness of managed futures funds is 0.9241 and the median is 0.6258. In comparison, Cai and Liang (2011) [26] find that managed futures funds are less likely to be dynamic funds. Hence, based on these observations, our measure of activeness shows some appealing properties.

In different market environments, hedge funds activeness should exhibit different features as hedge funds can react to changing market conditions quickly. We compute annual hedge fund activeness for each hedge fund year and take cross-sectional average within hedge fund styles each year. Figure 1 demonstrates how the hedge fund activeness varies over time for each hedge fund group. Our sample ranges from 1994 to 2013, covering the Asian financial crisis, the Technology Bubble and the 2008 global financial crisis.[8] We find that most hedge fund styles have more than one peak in their activeness during the sample period. More interestingly, these peaks tend to appear around frenzy times of the markets. For example, five out of the six hedge fund styles experience a spike in activeness in 2008. Security selection hedge funds experience the highest level of activeness around the technology bubble period. We do not wish to push this kind of interpretation too far, but we think the anecdotal coincidence with significant financial market events provides some support that our measure has the ability to capture hedge fund activeness.

[8]Since we have removed the first 12 monthly observations for each hedge fund in order to mitigate the backfilling bias, the actual data and the figure used starts from 1995.

#### 1.4.1.1 Persistence of Hedge Fund Activeness

If hedge fund activeness can potentially lead to superior performance, then those funds that are active in the past should remain active in the subsequent period, i.e, we should observe persistence in hedge fund activeness. To examine whether hedge fund activeness exhibits any persistence, at each month, we compute the activeness of each fund in the past twelve months. Besides, we calculate the activeness in the subsequent three months, six months, and twelve months. Then each month we assign funds into five quintile portfolios based on their past activeness. Next, we calculate the average past activeness as well as average subsequent activeness within each quintile. The Panel A of Table 3 reports equally-weighted average activeness while the Panel B presents value-weighted average activeness weighted by fund asset under management (AUM). In both panels, we observe that hedge fund activeness displays clear persistence. For example, funds that are the least active in the previous twelve months (Quintile 1) on average tend to remain the least active in the subsequent periods. The other four quintiles show the same pattern. In addition, the levels of activeness remain relatively stable for each quintile portfolio. The difference between quintile portfolio 5 and quintile portfolio is highly significant as indicated by the large values of *t*-statistics based on Newey and West (1987) [66] standard errors. Therefore, hedge fund activeness is quite persistent. Yet we still need to examine the relation between hedge fund activeness and performance.

#### 1.4.1.2 Determinants of Hedge Fund Activeness

Having examined the cross-sectional and time-series variation of hedge fund activeness, we next investigate the relation between hedge fund activeness and fund characteristics. Specifically, we regress the hedge fund future activeness on the past activeness as well as a number of fund characteristics according to Equation (1.5).[9]

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[9] In all regressions in this paper, we winsorize the dependent variables each period at the top 1 percentile and the bottom 1 percentile.

$$
\begin{aligned}
ACT_{t+1:t+12} &= \beta_1 ACT_{t-11:t} + \beta_2 CUMRET_{t-11:t} + \beta_3 VOL_{t-11:t} + \beta_4 RHO_{t-11:t} \\
&+ \beta_4 FLOW_{t-11:t} + \beta_5 LOGSIZE + \beta_6 AGE + \beta_7 LOCKUP + \beta_8 NOTICE \\
&+ \beta_9 MFEE + \beta_{10} PFEE + \beta_{11} OFFSHORE + STYLEDUMMIES + \epsilon \quad (1.5)
\end{aligned}
$$

$ACT_{t-11:t}$ is the activeness level in the past 12 months since we find that fund activeness is persistent. $CUMRET_{t-11:t}$ is the cumulative returns in the past 12 months. One probable reason of a hedge fund being active is to boost returns. Thus we expect that past performance would affect the level of activeness in the next period, although we are agnostic about the direction of the impact. Aragon and Nanda (2012) [10] study whether hedge funds exhibit "tournament behavior", i.e., poor-performing funds shifting to higher risk level. We also estimate a second version of Equation 1.5 with $CUMRET_{t-11:t}$ replaced by $PCTLRNK_{t-11:t}$, which is the percentile rank of past 12-month cumulative returns in month $t$, to study whether poor performance compared with peers induces funds to be more active. $VOL_{t-11:t}$ is past return volatility and $RHO_{t-11:t}$ is the first-order correlation of past reported returns. Getmansky et al. (2004) [45] demonstrate that the autocorrelation of hedge fund returns indicates the illiquidity of hedge fund assets. If assets held by hedge funds are not liquid, then it would be relatively more difficult to switch the positions. Thus illiquidity, proxied by the first-order autocorrelation, is expected to be negatively related to hedge fund activeness. Fund flows may influence hedge funds' trading activities. To examine the effect of flows on fund activeness, we include $FLOW_{t-11:t}$, the average monthly flow in the past 12 months, in Equation 1.5. Monthly flow is calculated as the percentage change in total net assets. We winsorize this variable at the 99% level to filter out outliers. Berk and Green (2004) [18] build a model in which mutual fund managers are subjected to diseconomy of scale. In the hedge fund industry, empirical evidence is also found that fund size erodes fund performance (See, e.g., Fung et al. (2008) [44]). As fund size increases, it becomes difficult to adjust positions actively. Hence the coefficient of fund size is expected to be negative. Older funds probably have established their reputation, and therefore they might be less active. The next two fund characteristics, the lock-up months and the notice period of redemption in 30 days, denoted by $LOCKUP$ and $NOTICE$, proxy for the hedge fund manager discretion (See, e.g., Agarwal et al. (2009) [4]). A manager with much discretion could implement investment strategies that otherwise she cannot. A distinguishing feature of hedge fund industry is that its fund managers are incentivized by the performance fees so that managers can get generous compensation if they achieve a high return. To earn the performance fee, hedge fund managers may actively change their positions in order to exploit as many opportunities as possible to make profits. So the performance fee may incentivize fund managers to be active. Lastly, we include style dummies to control for the style effect.

Table 4 contains the results for panel regression with time fixed effects. The standard errors are adjusted for fund-clustering effect following Petersen (2009) [70]. Not surprisingly, the coefficient of past activeness level is highly significant and positive yet less than 1, corroborating the finding that hedge fund activeness is persistent. The negative coefficient of past cumulative returns is significant at the $1\%$ level, suggesting that good past performance tends to reduce future activeness. In version (2) of Equation (1.5), percentile rank of past cumulative returns also takes on a significantly negative coefficient ($t$-statistic = -6.92). Past return volatility takes on a significantly positive coefficient. Though hedge funds often hold illiquid assets, the regression results show that autocorrelation in returns is positively related to activeness of hedge funds in the subsequent months. In Cai and Liang's (2011) [26] work, they also find that dynamic funds tend to have higher first-order autocorrelation. We note that hedge funds inflows tend to decrease the level of fund activeness. This makes sense as substantial fund inflows make it more difficult to actively manage the investments. The effect of fund size ($LOGSIZE$) on fund activeness is also negative and significant. As funds age, they become less active. This effect is very significant. A probable explanation is that fund age is associated with fund reputation and older funds with established reputation need not be as active as their younger peers. We also find that funds with longer lockup period tend to be more active as they have more discretion. Lastly, performance fee ($PFEE$) creates incentives for hedge funds to use all means, including actively change risk exposures, to achieve higher returns. The positive and significant coefficient suggests that hedge funds with higher performance fee tend to be more active.

In columns (3) and (4) Table 4, we interact fund past performance with fund characteristics to further examine the venue of the effect of past performance on subsequent fund activeness. The model is in (1.6).

$$\begin{aligned} ACT_{t+1:t+12} &= \beta_1 ACT_{t-11:t} + \beta_2 CUMRET_{t-11:t} + \beta_3 VOL_{t-11:t} + \beta_4 RHO_{t-11:t} \\ &+ \beta_5 FLOW_{t-11:t} + \beta_6 LOGSIZE + \beta_7 AGE + \beta_8 LOCKUP + \beta_9 NOTICE \\ &+ \beta_{10} MFEE + \beta_{11} PFEE + \beta_{12} OFFSHORE + \beta_{13} CUMRET_{t-11:t} * LOGSIZE \\ &+ \beta_{14} CUMRET_{t-11:t} * AGE + \beta_{15} CUMRET_{t-11:t} * LOCKUP + \beta_{16} CUMRET_{t-11:t} * NOTICE \\ &+ \beta_{17} CUMRET_{t-11:t} * MFEE + \beta_{18} CUMRET_{t-11:t} * PFEE \\ &+ \beta_{19} CUMRET_{t-11:t} * OFFSHORE + STYLE\,DUMMIES + \epsilon \end{aligned} \tag{1.6}$$

We note that the interaction of past performance with hedge fund size commands a significantly positive coefficient, suggesting that the dampening effect of past performance on subsequent activeness is less pronounced for larger funds. In addition, the interaction of past performance with hedge fund size commands a significantly negative coefficient. Thus, for a hedge fund with higher performance fee, good past performance induces a hedge fund to be less active in subsequent months.

### 1.4.2 Does Hedge Fund Activeness Yield Better Performance?

#### 1.4.2.1 Performance Measures

It is of particular interest to see if hedge fund activeness yield better performance and investors should systematically select active or inactive funds. We investigate this question by using several measures of performance. The first measure is the alpha. Monthly alphas are calculated as the difference between hedge fund returns and risk premiums. The second measure is the appraisal ratio calculated as mean of monthly abnormal returns divided by their standard deviation. Brown et al. (1995) [24]'s work shows that alpha scaled by idiosyncratic risk helps mitigate the survivorship problem. We use the Sharpe ratio as our third performance measure. Sharpe ratio is widely used to evaluate the risk-return trade-off of hedge fund performance.[10] The appraisal ratio and the Sharpe ratio also account for the effect of leverage. Goetzmann et al. (2007) [47] show that traditional performance measures can be gamed. Hence we use a fourth performance measure which is the manipulation-proof performance measure (MPPM) advocated by Goetzmann et al. (2007) [47]. It is calculated as

$$\hat{\theta} = \frac{1}{(1-\rho)\Delta t} ln(\frac{1}{T}\sum_{t=1}^{T}[(1+r_t)/(1+r_{ft})]^{1-\rho}) \tag{1.7}$$

In our case, $T = 12$ because we use the subsequent 12 months as the evaluation period; $\Delta t = 1/12$ as we have monthly hedge fund returns; and we choose 3 for $\rho$.

#### 1.4.2.2 Sorting-based Analysis

Starting from the twelfth month for each fund, we first calculate the activeness over the past 12 months and then sort hedge funds into quintile portfolios accordingly. As discussed in the previous subsection, we use four performance measures to analyze the relation between hedge fund activeness and performance. We calculate these four performance measures in the subsequent 12 months for each fund. For each quintile portfolio, we then compute the equal-weighted average of the the alpha, the appraisal ratio, the Sharpe ratio, and the MPPM within that quintile. Then we calculate the difference between quintile 5 (the most active hedge funds) and quintile 1 (the least active hedge funds) for each

[10] The Sharpe ratio here is defines as the mean monthly return divided by the volatility of monthly returns.

performance measure. To examine whether hedge fund activeness pays off, we examine how performance changes from the least active funds to the most active funds and test the difference of performance between the two extreme portfolios.

Table 5 contains the subsequent performance measures sorted on past hedge fund activeness and the *t*-statistics based on Newey-West standard errors. Column (1) shows the $\alpha$ of different hedge fund portfolios.The average subsequent alpha for the least active funds (i.e., quintile portfolio 1) is 0.47% per month while that of the most active funds (i.e., quintile portfolio 5) is 0.66%. The difference between these two groups is 0.19% per month, that is, 2.28% per annum. This difference is marginally statistically significant with a *t*-statistic of 1.72. Based on alpha, it seems that active hedge funds are associated with higher performance. We continue to look into other performance metrics. When the alpha is adjusted for the unsystematic risks that hedge funds take, the appraisal ratio shows a strong and a monotonically decreasing pattern from the least active hedge funds to the most active ones. The difference of the appraisal ratio between the most active funds and the lease active funds is -0.2822 (*t*-statistic = -9.18). Another risk-adjusted performance measure that we use is the Sharpe ratio. Similar to the appraisal ratio, the Sharpe ratio uniformly decreases with respect to the degree of activeness. The difference in the Sharpe ratio between the two extreme portfolios is also highly significant. Lastly, our fourth performance measure which is manipulation-proof also shows that the most active hedge funds tend to underperform inactive hedge funds. Overall, our sorting analysis paints a discouraging picture for the performance of funds that actively change their exposures to risk factors.

#### 1.4.2.3 Regression Analysis

Last subsection shows that hedge funds that are most active in changing risk exposures generally do not outperform the inactive ones over the entire sample period. Three out of the four performance measures actually show underperformance of hedge funds that actively change their factor exposures. In this subsection, we analyze the impact of hedge fund activeness on hedge fund performance through regression analysis controlling for a host of fund characteristics. Specifically, in the spirit of Titman and Tiu (2011) [75], we test whether hedge fund activeness can predict subsequent hedge fund performance. Our variable of main interest is the activeness in a 12-month period, which is calculated every month from December 1995 to December 2012. We conduct the Fama-MacBeth (1973) [35] regression and the panel regression to study the predictive ability of hedge fund activeness in the prior 12 months for hedge fund performance in the subsequent 12 months. We utilize the same four performance measures as in the previous subsection.

Similar to Equation (8) in Titman and Tiu (2011) [75], we regress hedge fund performance on prior hedge fund activeness and control variables that have been shown to be able to predict hedge fund performance.

$$Perf_{i,t+1:t+12} = Const. + \gamma ACT_{i,t-11:t} + \Theta X_{i,t} + \epsilon_{i,t} \tag{1.8}$$

where $Perf_{i,t+1:t+12}$ takes the form of raw return, alpha, the Sharpe ratio and the manipulation-proof performance measure with $\rho = 3$ ($\text{MPPM}_3$) for fund $i$ within month $t+1$ through month $t+12$. $ACT_{i,t-12:t}$ is the activeness of hedge fund $i$ in the 12-month period up to month $t$. $X_{i,t}$ indicates the set of control variables described as follows.

We include past performance to control for any persistence in hedge fund performance. We also include return volatility and average monthly fund flows in the previous 12 months. Bali et al. (2012) [15] document that return volatility has predictive ability for future hedge fund returns. Fund flows may affect fund managers' investment decisions thus affect fund performance. As discussed earlier, fund size can have a negative effect on fund performance because it becomes more difficult to fully exploit investment ideas without incurring substantial transaction costs if the fund is gigantic. We control for this effect by including $LOGSIZE$ which is the natural logarithm of fund size for fund$i$ at the end of month $t$. Aggarwal and Jorion (2010) [5] find that hedge funds tend to perform better at the early stage of their lives and the performance deteriorates as the fund ages. Therefore, $AGE$, which is fund $i$'s age in months at month $t$, is included to control for the age effect. Other control variables include management fee ($MFEE$) and performance fee ($PFEE$) in percentage, the redemption notice period in 30 days ($NOTICE$), the lockup period in months ($LOCKUP$) stipulated by the fund, and a dummy variable with 1 indicating offshore and 0 otherwise ($OFFSHORE$). To control for the style effect, we add seven dummy variables for the styles other than that defined as "other". Several studies (e.g., Cai and Liang (2011) [26] and Fung et al. (2008) [44]) find that the skill among hedge funds existed prior to the technology bubble and generally faded away after that. To investigate whether the impact of activeness on hedge fund performance exhibits different patterns over time, we split our sample into two uneven subsamples, one ranging from 1995 to 2002 and the other ranging from 2003 to 2013.

We report the Fama-MacBeth regression results in Table 6. The coefficients of style dummies are suppressed for brevity. Standard errors are corrected for serial correlation using the Newey-West procedure with 12 lags. The left panel of Table 6 is for the entire sample period January 1995—December 2013. We find that over the full sample period, past hedge fund activeness is able to predict the alpha during the subsequent 12 months. The coefficient is significant at the 5% significance level. However, one standard deviation increase in activeness leads to only 0.32% in alpha per annum, which is not economically significant. Besides, the significant positive relation is not found for other performance measures. In fact, hedge fund activeness is negatively associated with subsequent Sharpe ratio (*t*-statistic = -2.02). Past performance has strong predictive power for future performance, consistent with the findings of persistence in hedge fund performance by Jaganathan et al. (2010). Fund size is significantly negatively related to fund performance, indicating that large fund size imposes difficulty of actively managing fund capital. It is also shown that the coefficient of fund flows is uniformly negative, suggesting that fund flows pose difficulties for hedge funds to implement strategies. Managerial discretion proxied by lockup and notice period generally predicts positive performance. In addition, offshore funds tend to perform better than their onshore counterparts. The overall result for our primary variable–activeness–is mixed over the sample period 1995 to 2013, we then split our sample into two subperiods—pre-2002 period and post-2002 period to examine whether hedge fund activeness in adjusting risk exposures could ever lead to better performance. We first note that the signs and significance of the control variables remain relatively unchanged in the pre-2002 period. Furthermore, in the pre-2002 period, the magnitude of the positive impact of activeness on subsequent alpha is stronger. For example, an increase by one standard deviation of activeness in this period yields an increment of 0.81% in the alpha per annum. In the pre-2002 period, the coefficient of activeness for the appraisal ratio is also positively significant. Such results are in accordance with previous finding that hedge funds exhibit skills only in the period before the burst of technology bubble. However, we still do not find evidence of positive relation between hedge fund activeness and the Sharpe ratio and the manipulation-proof performance measure. In contrast, the results for activeness are quite different in the post-2002 period. In particular, the coefficients of activeness become negative though not statistically significant, suggesting that hedge fund activeness does not pay off in this period.

As Petersen (2009) [70] points out, if there exists fund fixed effect and it is not addressed, the standard errors would be biased. In addition to Fama-MacBeth regression, we also conduct the panel regression with the standard errors adjusted for fund clustering, as well as time fixed effect and style fixed effect. The results are reported in Table 7. Over the entire sample period, the activeness has a significant relation with only the Sharpe ratio and it is negative, suggesting more active funds tend to deliver lower Sharpe ratios. When we divide the sample period into pre-2002 period and post-2002 period, the impact of activeness on fund performance is dramatically different in these subsample periods. In the pre-2002 period, similar to the results in Table 6, we find that hedge fund activeness is positively associated with alpha and appraisal ratio. For example, in the pre-2002 period one standard deviation increase in hedge fund activeness yields an increment of 0.64% in alpha per annum, slightly less than the results in Table 6. Again, even in the pre-2002 period, hedge fund activeness does not lead to significantly greater Sharpe ratio or manipulation-proof performance. Table 7 suggests that, in the post-2002 period, activeness is negatively associated with all of the four performance measures except for alphas. In sum, we don't find evidence of active funds outperforming inactive funds. Even in the early sample period when hedge funds are documented to be able to deliver alpha, we don't find evidence of outperformance in terms of Sharpe ratio and the manipulation-proof performance measure.

## 1.5 Robustness Checks

In this section, we perform a number of robustness checks for the impact of hedge fund activeness on performance. We first examine how omitted factors would affect our results by including the trend-following factors advocated by Fung and Hsieh (2001, 2004). We then consider an alternative measure of hedge fund activeness and study its impact on hedge fund performance. Third, we exclude the years 2008 and 2009 to examine whether the relation between hedge fund activeness and performance is driven by the financial crisis. Finally, we look into the style-specific relation between hedge fund activeness and performance. We report panel regression results in Table 8.

### 1.5.1 Omitted Risk Factors

In previous sections, we computed and analyzed hedge fund activeness which is based on a set of linear risk factors. However, it is well-known that hedge funds often deliver a convex payoff. Researchers have devoted to constructing nonlinear factors to account for the nonlinear feature of hedge fund performance and the underlying systematic risk. In addition, Bollen (2012) [20] argues that it is likely that some risk factors are omitted when analyzing hedge fund performance due to the opacity of the hedge fund industry.

To alleviate the issue of leaving out potential risk factors, we include the nonlinear trend-following factors of Fung and Hsieh (2004) [43] and calculate hedge fund activeness.[11]

We repeat the panel regression analysis of the impact of hedge fund activeness on hedge fund performance using the exposures to risk factors that include the Fung and Hsieh (2004) nonlinear factors. The results are summarized in Panel A of Table 8. Compared with that in Table 7, the coefficient of activeness remains relatively similar in the full-sample regression. Again, the effect of activeness on hedge fund performance–alpha and appraisal ratio–is significant in the pre-2002 period. For instance, one standard deviation increase in activeness leads to an increment of 1.41% in alpha per annum. In the post technology bubble period, hedge fund activeness fails to generate greater performance as the coefficients of activeness are statistically and economically insignificant in all models. Therefore, our baseline results remain qualitatively intact as we include the Fung and Hsieh (2004) trend-following factors to estimate the time-varying risk exposures.

### 1.5.2 Alternative Measures of Activeness

We also consider another alternative measure of activeness. Specifically, we compute standard deviation of risk exposures within a twelve-month period and calculate the sum across risk factors, i.e., $\sum_{k=1}^{K} \sigma_{\beta_{k,t-11:t}}$. We find the correlation of this measure with the base measure of activeness is 0.93. With this measure of activeness, our panel regression analysis (results shown in Pane B of Table 8) continues to show that the relation between hedge fund activeness and performance is significant only in the pre-2002 period and that the magnitude of effect is similar, 0.76% increase in alpha per annum.

### 1.5.3 Excluding Years 2008 and 2009

Our results show that, in the post-2002 period hedge funds which are more active do not perform better. Ben-David et al. (2012) [17] find that during the financial crisis of

[11] We thank David Hsieh for making the data available on his website.

2007-2009 hedge funds were forced to sell a significant portion of their stock holdings due to redemptions and margin calls. Our results shown in Figure 1 are consistent with these findings. In fact, we show that many hedge fund styles traded abnormally actively in 2008. Though less severely than the stock market, the hedge fund industry still suffered substantial loss in the financial crisis. It is thus possible that we don't find evidence of positive relationship between hedge fund activeness and performance because of the extremely difficult environment for every one. Therefore, we investigate this possibility by excluding observations in years of 2008 and 2009, and conduct panel regressions and adjust the standard errors for fund clustering as well as time and style fixed effect as before. Results are reported in Panel C Table 8. However, we still don't find evidence of more active hedge funds generating better performance in the post-2002 period. When we conduct the Fama-MacBeth regression (results not shown here), we find that when excluding years 2008 and 2009, the coefficient of activeness becomes significantly negative for all of the four dependent variables except for the manipulation-proof performance measure. Therefore, we conclude that the negative relation between hedge fund activeness and performance in the post-2002 period is not driven by the crisis period.

### 1.5.4 Style Breakdown Analysis for Pre-2002 Period

So far our results show some evidence that hedge fund activeness yields better performance only in the pre-2002 period. However, does fund activeness lead to better performance for all fund investment styles in this period? Though we detect the activeness level, different fund styles may adjust factor exposures for different reasons. It is possible that activeness in adjusting risk exposures yields better performance for some styles while does not work for other styles. We check whether there is different impact across fund styles in this section. We report the panel regression results in Table 9. We are primarily interested in the interactions between fund activeness and fund styles. Table 9 shows that there is indeed cross-section difference among fund styles. Specifically, for directional traders, such as global macro funds, we find that the slope of activeness is significantly positive for the alpha, appraisal ratio and Sharpe ratio, although insignificantly positive for the manipulation-proof performance measure. Yet for non-directional styles such as the security selection style, the evidence that activeness yields better performance is much weaker.

## 1.6 Conclusion

This paper studies the activeness of hedge funds which is measured as the time-series average of sum of absolute changes in systematic risk exposures. To estimate time-varying hedge fund risk exposures, we first estimate covariance matrices of hedge fund returns and a set of risk factors using the dynamic conditional correlation approach advocated by Engle (2002). Then we apply the Bayesian information criterion to identify relevant risk factors for each month and obtain corresponding factor exposures. This method has the advantage of avoiding specifying an arbitrary regression window and accounting for the dynamics of both hedge fund exposures and asset class allocation. Simulation shows that the alpha does not increase with estimation errors.

We show cross-section dispersion in activeness across and within hedge fund investment styles. We also show variation of hedge fund activeness over time. The periods in which hedge funds exhibit particularly high activeness tend to coincide with the technology bubble and the 2008 financial crisis. In addition, hedge fund activeness is very persistent over time. We find good past performance and fund age have dampening effect on fund activeness while performance fee incentivizes hedge funds to be more active. Yet, conditional on good past performance, hedge funds tend with higher performance fee tend to be less active subsequently.

This study also investigates whether hedge fund activeness has the predictive power for the cross-section differences of hedge fund performance. Portfolio sorting analysis shows that activeness does not lead to superior hedge fund performance. Using the multivariate regression, we find a positive and significant link between hedge fund activeness and performance that only prevails in the sub-period prior to 2002. This pattern is robust for alternative measures of activeness. The insignificant relation between hedge fund activeness and performance in the post-2002 period is not due to the generally poor market conditions during the financial crisis of 2007-2009. We further examine the relation between activeness and performance in the pre-2002 period across fund investment styles. The results show that strategies that make directional bets exhibit a significantly positive slope for activeness.

# CHAPTER 2

# STOCK ANOMALIES AND CROSS-SECTION HEDGE FUNDS PERFORMANCE

## 2.1 Introduction

Market efficiency has been one of the center topics of finance academic research. Since Banz (1981) [16] documented the size effect, hundreds of other stock anomalies have been discovered[1]. Despite the fact that some of the documented anomalies might be a result of data snooping, there are still a number of stock characteristics that persistently predict cross-section stock returns and these phenomena cannot be explained by risks.

McLean and Pontiff (2015) [65] study whether the relations between return-predictive variables and stock returns persist after finance research uncovers them. They find significant decay of these relations. Their results are consistent with the idea that academic publications attract sophisticated investors to trade on these relations but their focus is not which type of investors does so. Hedge funds are usually viewed as arbitrageurs in financial markets that take advantage of inefficiencies in the market and get compensated by earning the risk-adjusted returns. Hedge fund managers often read academic papers and/or attend academic conferences to look for investment ideas. It is natural to think that hedge funds should have been exploiting the stock anomalies to enhance their risk-adjusted performance. Indeed, Akbas et al. (2015) [6] document a negative role of mutual fund flows in correcting stock market mispricing while a positive role of hedge fund flows in this process. Cao et al. (2015) [27] analyze hedge fund holdings and find that hedge funds tend to hold

[1] Green et al. (2013) [49] study more than 300 firm-specific characteristics that have been identified as predicting stock returns by academics and practitioners. Their results along with those of Green et al. (2014) [50] suggest that a number of strategies based on these characteristics could be profitable.

undervalued stocks and hedge fund trading precedes the dissipation of alpha. Taken these two pieces together, it suggests that "dumb money" help retain profitable arbitrage opportunities and sophisticated investors like hedge funds exploit these positive-alpha strategies. Green et al. (2014) [50] argue that practitioners, especially those who are quantitatively oriented, often have multiple return-predicting signals in their models. Motivated by these observations, in this paper, we examine whether the activities of hedge funds' exploitation of well-known stock anomalies can predict cross-section hedge fund performance.

We choose to work with ten variables that predict future stock returns. Namely, they are momentum, the accruals, the percent accruals, the total asset growth, the abnormal capital investment, the net operating assets, the return on assets, the net stock issuance, the gross profitability, and the sales-to-price ratio. This is only a small subset of variables that have been documented to be able to predict stock returns and whether exploiting these anomalies help hedge funds outperform is not known ex ante. But we posit that this would make the results weaker rather than stronger because this list is far from exhaustive of the many return-predicting variables uncovered.

We study this question by calculating a return-based measure for the intensiveness of hedge funds' activities in exploiting the afore-mentioned anomalies. We first construct anomaly factors following Fama and French (2015) [37]. Then we use the dynamic conditional beta method (Engle (2012) [34]) combined with the Bayesian information criteria to estimate time-varying exposures of hedge funds to selected anomalies. The sum of the estimated exposures each month is used to measure the intensiveness of hedge funds' activities in exploiting anomalies in that month, with a larger value meaning more intensively trading on anomalies. The performance metrics used in this paper are the Fama-French (1993) [36] three factor alpha and the appraisal ratio, which are also obtained by estimating the dynamic conditional beta model[2]. We then test whether the intensiveness of hedge funds' exploitation of stock anomalies in the prior twelve months (twelve-month average of monthly intensiveness) positively predicts risk-adjusted performance in the subsequent twelve months. We perform both portfolio sorts and multivariate regressions to test the relations. When conducting regression analysis, we employ the Fama and MacBeth (1973) [35] regression with *t*-statistic based on the Newey and West (1987) [66] standard errors and the panel regression with time fixed effect and *t*-statistic based on standard errors clustered at the fund level.

The sample we work on consists of 3024 equity-oriented hedge funds obtained from the CISDM and the Lipper TASS databases after imposing several mild data requirements for the purpose of meaningful estimation. The sample includes both live funds and defunct funds. The beginning of our sample period is January 1994 and the sample ends in June 2014.

We first examine whether hedge funds on average trade on these anomalies. To do so, we run a pooled regression of hedge fund excess returns on Fama-French (1993) [36] three factors and the ten anomaly factors and cluster the standard errors at the fund level. We find that our sample equity-oriented hedge funds are net long US equities, with a market beta of 0.33 and they tend to hold small stocks and growth stocks. As with anomalies, hedge funds seem to correctly trade on most of these anomalies as suggested by their significantly positive loadings, except for the percent accruals anomaly and the gross profitability anomaly. We also construct a combination factor that combines the ten anomalies by taking equal positions in these long-short strategies. The regression result suggests that hedge funds have a significantly positive exposure to this aggregate anomaly factor. The alpha also has decreased to some extent as we include the anomaly factors. This suggests that hedge funds

[2]Our results are robust to the estimation method. We also employ a rolling stepwise regression to estimate exposures to the anomaly factors and a rolling regression to estimate the alpha and the appraisal ratio. We obtain similar empirical results.

overall trade on the correct side of these anomalies and it corroborates the findings of Cao et al. (2015) [27].

We then proceed to study the main question of this paper–whether funds exploiting stock anomalies more intensively tend to outperform on a risk-adjusted basis. Our results support this view. Each month we sort hedge funds into deciles based on how intensively hedge funds exploit anomalies in the past twelve months, the alpha in the subsequent one month, three months, six months, and twelve months exhibits a near-monotone pattern. Over the subsequent twelve-month period, top decile funds, i.e., funds that most intensively exploit anomalies, tend to deliver 2.16 percent higher alpha on an annual basis than bottom decile funds. The difference of the annualized appraisal ratio between the tenth decile and the first decile of hedge funds is 0.17.

Controlling for a set of fund characteristics, we test the relation in a multivariate regression setting. Both the Fama-MacBeth regression and the panel regression indicate that there is a positive relation between hedge funds' exploitation of stock anomalies and hedge fund performance. Specifically, the coefficient of fund exploitation measure for subsequent alpha in the panel regression is 0.0929 ($t$-statistic = 3.28). Economically, this means that a one standard deviation increase in the measure of hedge fund exploiting stock anomalies would lead to an increment of 0.25 percent in alpha per annum, holding other things equal. The significance is robust to the distinctiveness of hedge fund strategies and the coefficient of determination (i.e., R-squared) for risk factors explaining hedge fund returns. The result for the appraisal ratio is weaker, with the coefficient being 0.0067 ($t$-statistic = 1.19).

Hedge funds and other institutional investors are often criticized for crowding into same positions which makes the strategies less profitable. We test this hypothesis. We construct a measure of strategy crowdedness also based on the time-varying anomaly exposure estimates. Our results show that the crowdedness of hedge fund strategies does exert a negative impact on the effectiveness of exploiting stock anomalies. The effect is more negative when the level of crowdedness is higher. For instance, when the level of crowdedness is relatively low (at the 25 percentile level), one standard deviation of increase in exploiting stock anomalies leads to additional 0.34 percent of alpha per annum. Nonetheless, when the level of crowdedness is relatively high (at the 75 percentile level), one standard deviation of increase in exploiting stock anomalies leads to additional 0.2 percent of alpha per annum. The marginal effect of a one standard deviation of increase in exploiting stock anomalies on the annualized appraisal ratio in these two cases is 0.021 and 0.001, respectively. Similarly, competition among hedge funds may also drive down the profitability of hedge fund strategies. We use the the average number of new equity-oriented hedge funds within a twelve-month period to proxy for the level of competition. The test shows that competition also negatively affects the performance of funds that exploit stock anomalies. We perform robustness checks using alternative measures and the results are similar.

Investor may fear that hedge fund exploiting anomalies, especially those that are quantitatively oriented, are more subject to downside risks. These funds may enter the same positions based on similar or same signals. Then one fund rewinding positions would impose price pressure on other funds' positions and thus trigger further unwinding, which would cause sharp decrease in the price of fund positions and substantial losses for these funds. Therefore, we also perform tests to examine how hedge funds' activities in exploiting stock anomalies as well as crowdedness would impact the skewness of hedge fund returns. We find that the exploitation of stock anomalies itself is positively related to the skewness of hedge fund returns, suggesting that such activities could enhance hedge fund performance. Although we do not find a significantly negative skewness because of crowdedness, we find that high levels of crowdedness of hedge fund strategies reduce the skewness of fund returns if hedge funds increase the intensiveness of exploiting anomalies.

Finally, we examine if investors reward hedge funds that more intensively exploit stock anomalies by investing more capital with these funds, since such funds appear to outperform others. The three measures of fund exploitation activities (including alternative measures) are not strongly related to fund flows in the subsequent three months and the subsequent twelve months. However, capital tends to flow out of funds that rely on taking systematic risks to generate returns.

Our work contributes to the literature in several ways. First, to our knowledge, we are the first one that link hedge funds' activities in exploiting stock anomalies with cross-section hedge fund performance. We find that such activities are beneficial for hedge fund performance. Although Titman and Tiu (2011) [75] show that skilled hedge funds tend to be those whose returns are achieved from sources other than systematic risk factors, our work extends theirs by looking into specific activities of hedge funds that lead to greater performance. When their measure (i.e., the R-squared) is included, our measure of hedge funds' activities in exploiting stock anomalies retains its predictive power. We also show that trading on anomalies and deviating from systematic risk (i.e., low R-squared) benefits higher moments–skewness, in particular, of hedge fund returns.

Second, our measure is based on returns rather than holdings. Hedge fund disclosure of their long positions provide opportunities for looking into their strategies and skills, but the picture is not complete without also analyzing their short positions. It is also more convenient to work with returns, especially if the information of fund holdings is not available.

Third, our work contributes to the debate of the role that hedge funds play in enhancing the market efficiency. The literature appears to disagree on whether institutional investors are rational and help eliminate mispricing in the market. Our results provide support for the recent findings that hedge funds behave rather differently than other institutional investors and they exploit stock anomalies. In addition, consistent with the argument of Grossman and Stiglitz (1980) [52] that costly searching of information should be compensated with positive returns, funds that trade on the mispricing tend to be rewarded with higher risk-adjusted performance such as the Fama-French alpha and the appraisal ratio.

The remaining of this paper is organized as follows. Section 2 reviews related literature on institutional investors and hedge funds. Section 3 discusses the methodology underlying this paper. Section 4 describes data. Section 5 presents tests on the relation between hedge funds' exploitation of anomalies and fund performance. Section 6 concludes.

## 2.2 Literature Review

Whether institutional investors play a role of helping eliminate mispricing in the financial markets is an important question and has been investigated by numerous studies. However, the results documented in the literature often suggest that institutional investors do not enhance market efficiency. For instance, Lewellen (2011) [61] show that institutional investors as a whole appear to hold a portfolio that resembles the market portfolio and institutions generally do not tilt their portfolios toward characteristics that predict stock returns. Similarly, Edelen et al. (2014) [32] find that institutional investors fail to tilt their portfolios to take advantage of anomalies. More pessimistically, the authors show that institutions generally trade contrary to what anomalies suggest, which means institutions tend to buy overvalued stocks and sell undervalued stocks. Avramov et al. (2015) [14] test whether active mutual funds overweight overpriced stocks and whether such activities can predict cross-section fund performance. They find that funds with high overpricing levels in their holdings tend perform poorly. These findings are corroborated by Akbas et al. (2015) [6] who show that "dumb money" proxied by mutual fund flows exacerbates mispricing in the stock market. But are hedge funds different, as they are often viewed as prototypical arbitrageurs? Brunnermeier and Nagel (2004) [25] show that hedge funds chose to ride the bubble before the technology bubble burst. Some recent studies indicate that hedge funds do contribute to the enhancement of market efficiency. Fodor et al. (2009) [38] investigate whether hedge funds arbitrage stock anomalies and find some supportive evidence. Green et al. (2009) [48] study whether hedge funds contribute to the demise of the accruals anomaly. Contrary to Ali et al. (2008) [7] who find that mutual funds overall do not exploit the accruals anomaly, Green et al. document that hedge funds exploiting activities are positively related to the demise of the accruals anomaly. Kokkonen and Suominen (2014)

[59] study whether hedge funds promote stock market efficiency. They use a market-wide measure of misvaluation based on the discounted residual income model and find evidence of hedge funds contributing to reduce mispricing in the stock market. Cao et al. (2015) [27] study whether hedge funds' holdings and trading help correct stock mispricing. They find that hedge funds tend to hold more undervalued stocks, i.e., stocks that exhibit positive alphas, and that hedge funds tend to bear the arbitrage costs, e.g., idiosyncratic risk, which Mashruwala et al. (2006) [63] argue potentially hinders the accruals anomaly from being arbitraged away. In comparison, they don't find significant and positive association of other institutional investors' trading with underpriced stocks. Similarly, Akbas et al. (2015) [6] report that hedge fund aggregate flows, contrary to mutual fund flows, contribute to the correction of mispricing in the stock market. Hwang and Liu (2014) [54] investigate short arbitrage activities and find that arbitrageurs do trade on anomalies, such as asset growth and firm investment. Therefore, hedge funds seem to play a very different role compared with other institutional investors, such as mutual funds, in the correction of mispricing in the stock market.

Despite the evidence of persistent positive-alpha opportunities and hedge funds exploiting mispricing, studies that focus on hedge fund manager skill are not unanimous about hedge funds' ability to deliver positive alphas for investors. Some research documents superiority of hedge funds in achieving risk-adjusted performance. For instance, Ackermann et al. (1999) [1] find that hedge funds tend to earn higher Sharpe ratio than mutual funds. Kosowski et al. (2006) [60] show that top hedge funds deliver higher abnormal performance and the source of the outperformance is skill. However, there are also some studies that cast doubt over the ability of hedge funds to deliver alpha (See, e.g., Asness et al. (2001) [12], Amin and Kat (2003) [9]). citeGX09 also question hedge fund managers' skill. Griffin and Xu examine hedge fund skills by looking into hedge fund holdings. They document that hedge funds have only marginal skills in stock picking and that skill is not dramatically superior to mutual fund sock-picking skill. Cao et al. (2014) [29] find that hedge funds prefer such stock characteristics as accruals, percent accruals, sales-to-price ratio. Nevertheless, they conclude that hedge funds prefer firm characteristics that predict lower volatility but not higher return. Others find that hedge funds historically deliver alpha only in a certain period of time and the alpha vanishes afterwards (e.g., Fung et al. (2008) [44], Cai and Liang (2011) [26]). We do not argue whether hedge funds as a group deliver abnormal performance for investors. Rather, we are interested in what differentiates hedge funds that are able to deliver risk-adjusted performance from those funds that are less good at doing so. In this regard, our work is related to Titman and Tiu (2011) [75] who show funds whose returns are less related to systematic risk factors tend to outperform and Sun et al. (2012) [74] who show that unique funds tend to outperform others. Aragon and Martin (2012) [11] document that hedge funds that utilize equity options are able to deliver higher risk-adjusted performance than nonusers of options. We study another particular kind of hedge fund activities–exploiting stock anomalies.

## 2.3 Methodology

In this paper, we are interested in the activities of hedge funds to exploit stock anomalies and whether such activities can predict cross-section hedge fund performance. Hedge funds usually do not just invest in one or few number of signals that predict stock returns but on the contrary exploit a (large) number of them. These signals include many stock anomalies. Given the large set of documented stock anomalies, it is not possible to analyze hedge funds' exploitation of each of the anomalies. Instead, we need to select some anomalies that are well-known to academics and professionals. We select ten stock anomalies. Namely, they are momentum, the accruals, the percent accruals, the total asset growth, the abnormal capital investment, the net operating assets, the return on assets, the net stock issuance, the gross profitability, and the sales-to-price ratio.[3]

[3]See Jegadeesh and Titman (1993), Sloan (1996), Hafzalla et al. (2011), Cooper et al. (2008), Titman et al. (2004), Hirshleifer et al. (2004), Pontiff and Woodgate (2008), Novy-Marx (2013). Though Brunnermeier

Whether the activities of hedge funds in exploiting stock anomalies predicts cross-section hedge fund performance is of interest in this paper. It is ideal to have data on hedge funds' stock holdings. However, hedge funds report their holdings at the firm level instead of at the fund level. Moreover, short positions are not required to be reported. Some research uses the short interest as a proxy for hedge funds' short positions to study hedge funds' role in driving security prices away from or towards the fundamental value. Since our research interest in this paper is different, we circumvent this issue by relying on the exposures of hedge funds to anomaly factors.

For each of these ten stock anomalies listed above except the momentum factor[4], we construct a long-short arbitrage portfolio and calculate its monthly returns. For the stock anomalies involving accounting data, we follow Fama and French (1993) by constructing portfolios at the end of June each year and calculate factor returns for the subsequent 12 months. This lag of at least 6 months ensures that the accounting information is available to fund managers when constructing portfolios. For example, for the accruals factor, we compute the sample firms' accruals using Sloan's formula at the end of June in year *t* using the balance sheet information of the fiscal year ending in year *t-1*. We then sort the stocks into three portfolios based on the past accruals and also sort stocks into small, medium, and large stock portfolios independently based on stock market capitalization at the end of each June[5], and calculate the value-weighted portfolio returns for each of the nine portfolios. Sloan shows that investors appear to be not able to fully absorb the information in accruals

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and Nagel (2004) find that hedge funs tend to hold low sales-to-price ratio (i.e., high P/S) stocks, this factor seems to be appreciated by the professionals. For example, O?Shaughnessy (2007) [67] calls it "the king of value factors".

[4]The Fama-French (1993) three factors and the momentum factor are obtained from Ken French's website, `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`. We thank Ken French for making these data available online.

[5]It is infeasible to obtain the factor returns that are orthogonal to all other factors by sorting, so we follow Fama and French (2015) [37] and Asness et al. (2013) [13] and double sort stocks on each characteristics and size. Since the multivariate regression coefficients pick up marginal effect and we focus on factor loadings, the correlation between factors should not have large effect on our results.

and firms with low accruals tend to outperform subsequently. So the strategy on accruals would be to long low-accruals (bottom) firms and short high-accruals (top) firm. The accruals factor would thus equals $\frac{1}{2}(LargeAccrualsBottom1 + SmallAccrualsBottom1) - \frac{1}{2}(LargeAccrualsTop3 + SmallAccrualsTop3)$. The breakpoints for accruals and stock market caps are both the 30th and 70th percentiles of NYSE stocks.

We then proceed with our analysis in two steps. First, we use the dynamic conditional beta (Engle (2012) [34]) combined with the Bayesian Information Criteria to estimate hedge funds' exposures to the anomalies. This approach enables us to dynamically select the anomalies that each fund trades on.

After obtaining time-varying exposures to the ten stock anomalies for each fund in our sample, we create a variable *Exploit* that measures the intensiveness of hedge funds trading on the ten anomalies for fund *i* in month *t* by adding up its estimated exposures to these anomalies, i.e.,

$$Exploit_{i,t} = \sum_{j=1}^{10} \beta_{i,j,t} \tag{2.1}$$

where $\beta_{i,j,t}$ is the coefficient of anomaly $j$ for fund $i$ in month $t$. In our empirical tests, we take the simple average of $Exploit_t$ over the past twelve months and test its predictive power for the fund risk-adjusted performance in the subsequent twelve months.

Second, we apply the dynamic conditional beta method on hedge fund excess returns and the Fama-French three factors only to get monthly alphas and further the appraisal ratio. These two performance metrics are then used in the portfolio sorting and the regression analysis.

## 2.4 Data

The data for hedge funds are from two commonly used databases for academic research regarding hedge funds: the CISDM and the Lipper TASS. The sample period spans from January 1994 and June 2014. We include both live funds and graveyard funds. Before 1994, data for graveyard funds are not available, which may cause survivorship bias. Since our main interest in this paper is hedge funds exploitation of stock anomalies, we focus on equity-oriented hedge funds. We only include the hedge funds whose base currency is the US dollar. We categorize a hedge fund as an equity-oriented hedge fund primarily based on the classification made by CISDM and TASS. More specifically, hedge funds in CISDM that are categorized as Global Long/Short Equity, Long-Only Equity, Equity Market Neutral, U.S. Long/Short Equity, or U.S. Small Cap Long/Short Equity, and hedge funds in TASS that are categorized as Long/Short Equity Hedge or Equity Market Neutral, are classified in this paper as equity-oriented funds. As outlined in the previous section, our measure of hedge fund exploiting stock anomalies relies on the time-varying factor loadings estimated by using the dynamic conditional beta method and selecting factors using the Bayesian Information Criteria, thus to obtain meaningful estimates of the time-varying factor loadings, we require that for a fund to be included in our sample it must have an average of asset under management no less than $5 million and have at least 36 consecutive net-of-fee monthly returns. Our final sample includes 3024 equity-oriented hedge funds.[6]

Data for stock returns and annual accounting information are downloaded from CRSP and COMPUSTAT, respectively. We include only common stocks (with share code 10 and 11) that are listed in NYSE, AMEX, and NASDAQ. To be included in our sample, the stock must be in the COMPUSTAT database for at least two years when the portfolios are formed. We exclude financial firms with SIC codes between 6000 and 6999.

Table 10 presents the summary statistics of hedge fund returns and characteristics. We have 307,992 monthly observations of net-of-fee returns for the 3024 equity-oriented hedge funds in our sample. The mean return of all the sample funds over our sample period is 0.88% and the median is 0.77%. The second row shows the skewness of our sample hedge funds. The skewness is calculated using all returns of each fund. The average skewness

[6]Cao et al. (2013) [28] has a broader definition of equity-oriented hedge funds. We choose to work with a narrower definition because we rely on the loadings to the stock anomaly factors.

across all funds is slightly negative, -0.02, and so is the median skewness, -0.06. Since we demand that each hedge fund must have an average asset under management of over five million US dollars, the average size of the sample funds is shifted upward slightly. Across all funds the overall average size is $101.82 MM and the median number is $87 MM, suggesting that some funds in our sample are quite large. Recall that we also require that funds must have more than 36 consecutive monthly return observations to be included in the sample. Most hedge funds in our sample actually have more than 60 observations. Hedge funds are well-known for charging investors both the management fee and the performance fee. In our sample, most funds charge a management fee that is below 2%, with the mean of 1.37% and the median of 1.50%. However, they typically charge performance fee of 20%. Since hedge funds often charge performance-based fees, it is important to make sure that hedge funds do not get paid for what they have already been paid for. High water mark is used to this end–only the portion beyond the highest value the fund has achieved is rewarded. The *HighWatermark* in the seventh row of Table 10 is a dummy variable with 1 indicating the high water mark is adopted by the fund and 0 otherwise. It shows that more than three quarters of the funds have the high water mark design in place. Another feature of hedge funds is that they typically stipulate a restriction period for the capital invested in the hedge funds to ensure that they can fully implement their investment strategies, without having to worry about liquidating their positions to meet investors' liquidity needs and suffer unnecessary losses. The lockup period and the redemption notice period are the two most famous means of capital restriction. For example, the hedge funds in our sample impose an average lockup period of 5.23 months. Though many funds choose to not have the lockup period, the vast majority of them require that investors inform the funds in advance of the redemption needs. The average length of the redemption notice period is 38 days and over half of the funds stipulate a notice period of more than 30 days. Finally, nearly half of the hedge funds in our sample are offshore funds domiciled outside the US.

In Table 11, we report the summary statistics of the Fama-French factors and the anomaly factors. Panel A shows the average monthly returns and the Sharpe ratio of the factors. All of these factors have positive mean returns. Moreover, the mean returns of the anomaly factors (except for ROA, return on assets) are greater than the mean returns of the size factor and the book-to-market ratio factor. We also compare the Sharpe ratio of these factors. The anomaly factors overall deliver greater Sharpe ratios than the size and the book-to-market ratio factor. For example, the Sharpe ratio of the net operating assets factor (NOA) is 0.18, nearly three times of the Sharpe ratio of the size factor. The last two rows of Panel A Table 11 report the Fama-French alphas of the ten anomalies and their $t$-statistics. Most anomaly factors exhibit significant and positive alphas. In Panel B Table 11, we report the correlation among the Fama-French three factors and the anomaly factors. Generally, the anomaly factors have quite low correlation with the three risk factors and sometimes the correlation is negative. Among the anomaly factors, the correlation is also generally low though for some factors the correlation can be as high as over 0.6 in absolute value. We allow for some correlation among the factors as we believe the estimated loadings on selected factors pick up the marginal effect of these factors. The last column of Table 11 is the factor by taking equally-weighted positions in the ten individual anomaly strategies. This combined factor exhibits higher Sharpe ratio than individual factors and highly significant alpha. It also has low correlation with the Fama-French factors. The high performance of these anomaly factors and the low correlation with the market suggest that trading on anomaly factors may enhance hedge fund performance.

## 2.5 Empirical Results

### 2.5.1 Do Hedge Funds Exploit These Anomalies?

We begin our empirical analysis by examining whether hedge funds exploit the anomalies chosen in this paper. Although institutional investors as a whole are often documented to exacerbate the mispricing in the market, hedge funds could be different. First, hedge funds are marketed as delivering absolute returns, so they should look for arbitrage opportunities and exploit them once they find any. The finance literature has shown a number of opportunities that stem from the market inefficiency (See, e.g., Green et al. (2013) [49]), suggesting that strategies on exploiting market mispricing are feasible. Second, hedge funds are relatively lightly regulated, especially in shorting securities. The arbitrage profits are often more notable on the short side of the strategy, so the ability to short enables hedge funds to more fully exploit the mispricing that exists in the financial markets.

We regress hedge fund returns (in excess of risk-free rate) on Fama-French factors and anomaly factors. If hedge funds trade on the correct side of anomalies, then the loadings on the anomalies should be positive. Table 12 reports the results of pooled regressions with standard errors clustered at the fund level. The Column (1) presents regression results with the Fama-French three factors only. It shows that the sample equity-oriented hedge funds are net long to the US equity market and they tend to prefer small stocks over large stocks and growth stocks over value stocks. The intercept is 0.0033 and highly statistically significant. In Column (2), we include the anomaly factors. We find that on average hedge funds trade on the right side of most of the anomalies. They tend to hold past winners over past losers, and net long stocks with low accruals, low asset growth, low capital investment, low net operating assets, high return on assets, low stock issuance, and high sales-to-price ratio. However, the hedge funds seem to be net longing less profitable stocks and stocks with high percent accruals. The intercept is 0.0029, slightly less than the constant in Column (1) and still statistically significant, suggesting that there might exist other alpha-generating strategies that hedge fund employ. However, the difference is statistically significant ($z$-statistic = 2.78). In Column 3, we replace the individual anomaly factors with the combined anomaly factor. We find that the loading on the combined anomaly factor is also positive and statistically significant, which confirms that hedge funds not only exploit stock anomalies but also trade on the correct side of the anomaly strategies. The intercept is 0.0027 and it's statistically significant ($z$-statistic = 4.61). Therefore, our results corroborate the findings of Cao et al. (2015) [27] and we expect that hedge funds that exploit anomalies receive compensation in the form of higher risk-adjusted performance.

### 2.5.2 Characteristics of Hedge Fund Activities in Exploiting Stock Anomalies

In this subsection, we first explore the characteristics of hedge funds' activities in exploiting stock anomalies. The measure of exploiting anomalies is described in Section 3. If hedge funds systematically involve in exploiting stock anomalies in the market, we should expect to see a relatively persistent pattern in such activities. To examine the persistence of hedge funds exploiting activities, each period we sort hedge funds based on the *Exploit* during the past twelve months into four quartile portfolios and examine which quatiles these funds fall into due to the level of *Exploit* in the subsequent 12 months. Panel A of Table 13 presents the transition matrix for *Exploit*. It indicates that hedge funds are more likely to keep the level of their activities in exploiting market inefficiencies. For example, hedge funds in the extreme quartiles, either the most active ones or the least active ones, have a probability of over 0.65 to continue to be the most (or the least) active ones in the subsequent period. And it is rather unlikely for these funds to completely change their style or involvement in exploiting stock anomalies in the subsequent period. For hedge funds that fall in the middle deciles, although the probability of they staying in the same quartiles subsequently is lower compared with extreme quartiles, they are more likely to fall into adjacent quartiles and much less likely to fall into extreme quariles.

Then we further link such activities with various hedge fund characteristics as in Equation (2.3).

$$Exploit_{t+1:t+12} = a + bExploit_{t-11:t} + c'X_t + \epsilon_t \tag{2.2}$$

We conduct both Fama-MacBeth (1973) regression and panel regression with time fixed effect, with the subsequent exploiting activities being the dependent variable, and show the results in Panel B of Table 13. Column 1 shows the Fama-MacBeth regression results and the *t*-statistic is based on Newey-West (1987) standard errors. The coefficient of the previous exploiting activities is significantly positive and less than 1, suggesting that hedge funds tend to be persistent in their activities in exploiting stock anomalies. This is consistent with what we see in Panel A of Table 13. In addition to the past level of exploiting activities, we also include past alpha which is the past twelve-month average of fund excess return minus risk premiums gained from loading on Fama-French (1993) three factors, and the natural logarithm of fund age and asset under management at month *t*, fees charged by hedge funds, high water mark, lockup months, redemption notice period (in days), as well as a dummy variable *Offshore* with 1 for funds whose domicile is outside of the US and 0 otherwise. Among these fund characteristics, we find that performance fee and the redemption notice period have significant and positive coefficients. The latter result is in line with Giannetti and Kahraman (2014) [46] who find that hedge funds with higher share restrictions are more intensively involved in trading against mispriced stocks. Combining with results in the second column which shows panel regression with *t*-statistics based on standard errors clustered at the fund level, we confirm that past level of exploiting activities, performance fee, and redemption notice period are positively related to the subsequent activities in exploiting stock anomalies.

### 2.5.3 Exploiting Anomalies and Fund Performance

How hedge funds' activities in exploiting stock market anomalies impact fund performance is of our primary interest. We utilize both the portfolio sorts method and the multivariate regression analysis to study this question. We employ *alpha* derived from the FF model and *appraisal ratio* as our performance metrics, where $alpha_t = Ret_t - b_t(R_{M,t} - R_{f,t}) - s_t SMB_t - h_t HML_t$ and $Ret_t$ is the fund excess return in month *t*. To guard the results against being driven by outliers, we winsorize the performance metrics and our measure of hedge funds activities of exploiting stock anomalies at the top and bottom 0.5 percent each period.[7]

**Sorts**. Each month we sort hedge funds into decile portfolios based on the measure of fund exploiting stock anomalies in the past twelve months, and we examine how the performance metrics, namely, the *alpha* in the subsequent month, 3 months, 6 months, and 12 months, as well as the *appraisal ratio* in the subsequent 12 months[8], change across the ten deciles. Table 14 contains the results of portfolio sorts. Performance metrics are equally weighted within each decile. Decile 1 includes funds that exploit stock anomalies the least intensely and decile 10 includes those that trade on anomalies the most aggressively. Columns 1 through 4 present alphas in the subsequent 1, 3, 6, and 12 months. There is a near-monotonic pattern in alpha across the 10 decile fund portfolios. Funds that are relatively less aggressive in exploiting anomalies tend to deliver lower alphas while funds that are more aggressive tend to deliver higher alpha. This pattern is stable over time as we observe such a pattern in all the first four columns. In the extreme deciles, the decile 1 portfolio delivers monthly alpha of 0.31% and the decile 10 portfolio delivers monthly alpha of about 0.50%. The difference between the two deciles is about 0.18% per month in the subsequent 12 months (2.16% annually) and it is also statistically significant as the $t$-statistic based on the Newey-West standard errors is above 2. Column 5 compares the appraisal ratio of the ten deciles. Though we do not observe a monotonically increasing pattern from decile 1 to decile 10 and it appears the middle deciles have the highest appraisal ratio, we find that the difference of the appraisal Ratio between decile 10 and decile 1 is statistically different ($t$-statistic = 3.22).

**Multivariate Regression**. The non-parametric sorting appears to show that there is a positive relation between hedge funds' exploiting stock market anomalies and fund per-

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[7]We choose top and bottom 0.5 percent because the data at these percentiles are not extreme. The results from winsorizing data at the top and bottom 1 percent each period remain very similar.

[8]The alpha in the subsequent 3 months equals the average of monthly alphas in those months. The same applies for alphas in the subsequent 6 months and 12 months

formance, especially for the alpha and the appraisal ratio. Next, we conduct multivariate regressions to analyze the relation when a set of control variables is included. We first estimate the Fama-MacBeth regression.

$$Perf_{i,t+1:t+12} = Const + \gamma Exploit_{i,t-11:t} + \theta' X_{i,t} + \epsilon_{i,t} \tag{2.3}$$

We report the results in Table 15. The *t*-statistics are based on the Newey-West standard errors to account for the heteroskedastisity and autocorrelation.

The dependent variable in Model 1 (Column 1) is the alpha in the subsequent 12 months. The coefficient of $Exploit_{t-11:t}$ is 0.1244 and statistically significant (*t*-statistic = 2.42). This confirms the positive relationship between hedge funds' activities in exploiting stock mispricing and fund performance. One standard deviation of increase in $Exploit$ would lead to 0.33 percent of increase in annualized alpha in the subsequent 12 months. The variable *Distinct* is Sun et al.'s (2012) measure which is computed as 1 minus the correlation coefficient of the past 12-month fund returns and past 12-month average equity-oriented fund returns. It measures how unique a fund is compared with its peers. We find that the coefficient of $Distinct$ is positive yet not statistically significant. Titman and Tiu (2011) argue if a fund delivers returns by taking on systematic returns and thus variation in returns can be explained to a large extent by variations in risk factors then this fund is not likely to deliver significant risk-adjusted returns in the future. Consistent with this hypothesis, they find that the *R-squared* derived from regressing hedge fund returns on risk factors negatively predicts future fund performance. Titman and Tiu's measure appears to be similar to ours–if a fund generates returns mainly from exploiting stock anomalies, then the *R-squared* of regressing fund returns on Fama-French three actors should be low. We include the *R-squared* which is obtained from regressing each fund's past 12-month returns on the Fama-French three factors. As expected, *R-squared* is negatively related to future fund alphas and the coefficient is highly statistically significant. In addition, we also control for fund characteristics. *LogAge* and *LogAsset* are natural logarithms of fund age and asset under management, respectively. Their coefficients are significantly negative, suggesting that young and small funds tend to generate higher alphas. Management fee (*MFee*) also has a significantly positive coefficient. Performance fee (*PFee*) and high water mark (*HighWatermark*) provide incentives for fund managers to deliver better performance. We find that they both have significantly positive coefficients. Redemption notice period (*NoticePeriod*) also commands a significantly positive coefficient, suggesting that hedge funds that have longer advance notice period of redemption tend to deliver higher alphas. The dependent variable in Model (2) (Column 2) is the appraisal ratio. The results are weaker. After controlling for Sun et al.'s distinctiveness and Titman and Tiu's R-squared, as well as fund characteristics, the measure for hedge funds exploiting stock anomalies has a positive coefficient that is not statistically significant ($t$-statistic = 1.48). The distinctiveness is not statistically different from 0 albeit slightly positive, and the R-squared is significantly negative, which is consistent with our expectation.

In Table 16, we show the results from panel regression with the same dependent variables and independent variables as in Table 15. We include time fixed effect and cluster the standard errors at the fund level in case there exists fund fixed effect. The performance metrics are alpha and appraisal ratio, respectively. In Column 1, the coefficient of $Exploit_{t-11:t}$ is 0.0929 with a $t$-statistic of 3.28. Compared with that in the Fama-MacBeth regression, the magnitude of the coefficient is similar. The distinctiveness measure continues to be not significantly different from 0. On the contrary, *R-squared* commands a significantly negative coefficient ($t$-statistic = -8.12), which is consistent with Titman and Tiu's findings. The coefficients for other fund characteristics are similar to those in the Fama-MacBeth regression. In Column 2 where the appraisal ratio is the dependent variable, the magnitude of the coefficient of fund exploitation activities has decreased relative to that in Table 15, and it is still statistically insignificant, with a $t$-statistic of 1.19, suggesting a weak relationship between fund exploitation activities and the subsequent appraisal ratio.

The results shown in tables 14 through 16 so far suggest that hedge funds that exploit stock anomalies tend to earn higher risk-adjusted returns subsequently. However, the positive relation between the activities of exploiting stock anomalies and the appraisal ratio is a little weak.

### 2.5.4 Crowded Trading and Competition

When hedge funds herd into the same strategies, those strategies become less profitable. For example, Green et al. (2009) show that the famous accruals anomaly has become less profitable over time in their sample period and they attribute it to hedge fund investment. Therefore in this section we test the hypothesis that crowdedness exert a negative impact on the effectiveness of exploiting stock anomalies, especially for those that trade stock anomalies more aggressively. To do so, we construct a measure of crowdedness based on our time-varying estimates of hedge fund exposures to the anomaly factors. We view the strategy is more crowded if there is less variation in cross-section hedge fund exposure to that strategy. This measure is in the spirit of the measure for dispersion in analyst opinions. Specifically, for each anomaly each month, we calculate the mean and the standard deviation of hedge fund exposure to that anomaly and take the ratio of the two. Then we take the average of the ten individual crowdedness measure to proxy for the aggregate state of crowdedness of hedge funds strategies. The formula is given in Equation (2.4):

$$Crowd_t = \frac{1}{10} \sum_{j=1}^{10} \frac{Mean(\beta_{i,j,t})}{Std(\beta_{i,j,t})} \tag{2.4}$$

where $\beta_{i,j,t}$ is the exposure of fund *i* to the anomaly factor *j* in month *t*. If the cross-sectional standard deviation of exposures is small relative to the mean, then the $Crowd_t$ would be relatively high and it indicates the strategy is relatively crowded. To be consistent with our measure of hedge fund exploitation activities, we use the rolling twelve-month average of the $Crowd_t$ in our tests. We expect that the extent to which hedge funds pursue the same profit opportunities would weaken the relation between exploiting stock anomalies and subsequent fund performance.

The hedge fund industry has grown rapidly in the past two decades, with assets under management exceeding $3 trillion as of the third quarter of 2015 according to BarclayHedge. Equity-oriented hedge funds are the most populous group among all hedge fund styles. New funds keep being launched and the competition is fierce since this industry is viewed lucrative. We hypothesize that when there is greater level of competition proxied by the natural logarithm of the average number of new equity-oriented funds launched in a twelve-month rolling window, it would negatively affect the effectiveness of funds exploiting mispriced stocks in the market.

The panel regression results for these tests are reported in Table 17. Columns 1 and 2 are for alpha, and Columns 3 and 4 are for the appraisal ratio. The coefficient of *Exploit* is positive for alpha and the appraisal ratio, and it measures the marginal effect of exploiting stock anomalies on fund performance when the crowdedness or the competition is at the historical mean level. This coefficient is statistically significant for alpha but just marginally significant for appraisal ratio. Our primary interest in this subsection is the coefficient of the the interaction term between *Exploit* and crowdedness of trading (*Crowd*) and competition (*Newfund*). As expected, in Column (1) of Table 17, the interaction term between *Exploit* and *Crowd* is negative, however, it is not statistically significant ($t$-statistic = -1.52). In Column (2), we observe that the interaction between *Exploit* and *Newfund* is significantly negative ($t$-statistic = -2.07), suggesting that intense competition erodes profit opportunities. To put these numbers in economic perspectives, we compute and test the marginal effect of exploiting stock anomalies on fund performance at the high and low levels of crowdedness and competition. For instance, at the low level of crowdedness (e.g., the 25th percentile), a one standard deviation of increase in exploiting stock anomalies would bring about an increase of 0.34 percent in alpha per annum ($t$-statistic = 3.24). At the 75th percentile of crowdedness, a one standard deviation of increase in exploiting stock anomalies would bring about an increase of 0.2 percent in alpha per annum ($t$-statistic = 3.03).When the competition is more intense as measured by more newly-launched funds (e.g., at the 75th percentile), one standard deviation of increase in exploiting stock anomalies would bring about an increase of 0.13 percent in alpha per annum ($t$-statistic = 1.72), compared with an increase of 0.40 percent ($t$-statistic = 3.29) in alpha when *Newfund* is at the 25th percentile.

In Column 3 where the appraisal ratio is the dependent variable, the coefficient of the interaction term between *Exploit* and *Crowd* is -0.1411 and it is significant at the 1% level with a $t$-statistic of -4.22, suggesting that crowdedness of hedge fund trading has a negative effect on the effectiveness of trading on stock anomalies to enhance the appraisal ratio of hedge funds. The marginal effect of a one standard deviation of increase in exploiting stock anomalies on the annualized appraisal ratio is 0.021 ($t$-statistic = 3.45) and 0.001 ($t$-statistic = 0.16), respectively, when *Crowd* is at the 25th percentile and at the 75th percentile. As for the effect of competition, the results in Column (4) show that the interaction term of *Exploit* and *Newfund* is negative and significant at the 1% level. When the level of competition is low (e.g., at the 25th percentile), a one standard deviation of increase in the exploiting activities increases the appraisal ratio by 0.023 per annum ($t$-statistic = 3.28). When the level of competition is high (e.g., at the 75th percentile), a one standard deviation of increase in the exploiting activities decreases the appraisal ratio by 0.008 per annum ($t$-statistic = -1.44).

Overall, we find some evidence that crowdedness of hedge fund strategies and competition have some negative effect on the performance of funds that exploit stock market anomalies. The competition seems to erode the profits of exploiting stock anomalies.

### 2.5.5 Alternative Measures for Exploiting Anomalies

For robustness, we compute two alternative measures for hedge funds' activities in exploiting stock anomalies. Since these anomaly strategies on average deliver positive returns, we presume the exposure to these anomaly factors should be positive if the fund managers do not attempt to time these factors. Thus our first alternative measure considers only the sign of the exposures. For a particular anomaly in a period, we assign 1 if the estimated exposure is positive and 0 otherwise. Then we sum across the anomalies and take the average. So the *involvement* of fund *i* in exploiting anomalies in month *t* is given by Equation (2.5)

$$Involve_{i,t} = \frac{1}{10}\sum_{j=1}^{10} I(\beta_{i,j,t} > 0) \tag{2.5}$$

where $I(\cdot)$ is an indicator function. We then examine the predictive power of the average of $Involve_t$ in the past twelve months for the fund performance in the subsequent 12 months, and investigate the effect of crowdedness and competition. The correlation of this alternative measure with *Exploit* is 0.68.

The results are reported in Table 18 where we observe very similar patterns for the coefficients. *Involve* commands a positive coefficient in these specifications despite its marginal significance for the appraisal ratio. Interactions of *Involve* with *Crowd* and *Newfund* have negative coefficients, confirming the negative impact of strategy crowdedness and competition on the effectiveness of exploiting stock anomalies.

Our second alternative measure is based on the exposure to the combined anomaly factor as in Table 12. The combined anomaly factor, which is the equal-weighted average of anomaly returns in any given month, aggregates the information of the ten individual anomaly factors, so the exposure to the combined factor reflects whether, and to what extent, hedge funds trade on stock anomalies. Thus we first estimate the time-varying exposures to the combined anomaly factor for each fund using the dynamic conditional beta method and calculate the rolling twelve-month average of the exposures. We then repeat the panel regressions as in Table 17 and in Table 18. Results shown in Table 19 indicate a strong and positive relation between exploiting stock anomalies (*BCOMB*) and fund performance. Moreover, high levels of crowdedness and competition would weaken the prior positive relation. We also find similar marginal effect of the two alternative measures of hedge fund trading on anomalies when accounting for the effect of crowdedness and competition.

### 2.5.6 Does Funds Exploiting Anomalies Affect Skewness of Fund Returns?

Hedge funds are supposed to deliver returns not related to systematic risks, and the anomalies that exist in the stock market clearly present good opportunities for these sophisticated investors. As sophisticated as hedge funds could be, however, they may not know how many of their peers are doing the same thing (Stein (2009) [73]). When hedge funds enter the same trade, there might exist substantial downside risk for the stocks these funds hold, especially when one fund's sale triggers other funds unwinding as well, which in turn may have a negative impact on fund performance. Khandani and Lo (2007) [58] study what caused the noteworthy losses for the equity long/short hedge funds, especially those who are quantitatively oriented, within a short period of time in August 2007. They find evidence supporting the conjecture that large overlaps of portfolios are subject to negative price pressure when there is liquidation by others. The identified anomalies are public information to all funds, so it is likely that a number of hedge funds end up with similar portfolios due to similar signals, even though hedge funds may modify the anomaly signals. We have shown that crowdedness of strategies is detrimental to hedge fund performance. In this section, we examine the role of exploitation activities of anomalies and the crowdedness in affecting the higher moments of hedge fund performance–skewness. We run the following panel regression (Equation (2.6)) with time fixed effect and report the results in Table 20. The dependent variable is the skewness of the hedge fund returns in the subsequent 24 months. The results are shown in Column (1) of Table 20.

$$Skew_{i,t+1:t+24} = \gamma Exploit_{i,t-11:t} + \delta Crowd + \eta Exploit_{i,t-11:t} * Crowd + \theta' X_{i,t} + \epsilon_{i,t} \quad (2.6)$$

We find that hedge funds' activities in exploiting stock market anomalies appear to be positively related to the skewness of hedge fund returns but not statistically significant. The coefficient of $Exploit$ is 0.0435 with the *t*-statistic of 2.59. However, the negative coefficient of the interaction term is -0.2259 (*t*-statistic = -2.29). This suggests that the effect of exploiting stock anomalies on the skewness of hedge fund returns depends on the extent to which hedge funds employ similar strategies. When the level of crowdedness of hedge fund strategies is relatively low (e.g., at 25 percentile), exploiting stock anomalies might benefit investors in terms of higher likelihood of profits and it is consistent with previous findings that such activities enhance hedge fund risk-adjusted performance–a one standard deviation increase in the intensiveness in exploiting stock anomalies would increase the skewness of hedge fund returns by about 0.014 (*t*-statistic = 2.95). Conversely, When the level of crowdedness of hedge fund strategies is relatively high (e.g., at 75 percentile), the marginal effect of a one standard deviation increase in the intensiveness in exploiting stock anomalies on subsequent return skewness is 0.005 (*t*-statistic = 1.38). This provides some evidence to the conventional wisdom that hedge funds piling into same strategies is subject to the risk of suffering dramatic losses. Interestingly, the *R-squared* commands a negative coefficient that is statistically significant. Lower *R-squared* means the hedge fund generates return mostly from sources other than taking on systematic risks. It has been shown that such funds tend to outperform in terms of risk-adjusted performance. We show that these funds are also less likely to experience large losses.

We then repeat the regression (2.6) using the two alternative measure as in subsection 2.5.5. The corresponding results are shown in Columns (2) and (3) of Table 20. Similar to the results in Column (1), the two alternative measures of exploiting stock anomalies are statistically distinguishable from 0. The significantly negative coefficient of the interaction term between crowdedness of hedge fund strategies and intensiveness of hedge funds exploiting stock anomalies confirms the findings in Column (1) that funds which intensively trade on stock anomalies when those strategies are crowded are more subject to more negatively skewed returns.

### 2.5.7 Do Investors Acknowledge Funds' Activities in Exploiting Anomalies?

We have shown that exploiting stock anomalies could be beneficial for hedge fund risk-adjusted performance. However, it is not clear whether investors are aware of the advantages of hedge funds spending resources on exploiting mispricing in the marketplace. On the other hand, the "quant meltdown" seems to have made investors cautious about quantitative hedge funds that tend to employ similar methods. In this section, we examine the flows to the hedge funds that trade on stock anomalies.

Specifically, we run the following panel regression (Equation (2.7)) to test if the fund flows are related to the intensiveness of hedge funds exploiting stock anomalies and how investors react on the crowdedness of hedge fund strategies[9].

$$Flow_{i,t+1:t+j} = b_1 Exploit_{i,t-11:t} + b_2 Crowd + b_3 Exploit_{i,t-11:t} * Crowd + b' X_{i,t} + \epsilon_{i,t}, \quad j = 3, 12 \tag{2.7}$$

The dependent variable is the average monthly fund flows in the subsequent three months or twelve months. We also run the above regression with the two alternative measures of hedge fund intensiveness of trading on stock anomalies.

The results are shown in Table 21 where the first three columns are for the average monthly fund flows in the subsequent three months and the last three columns for the subsequent twelve months. In the six specifications, we find that none of the coefficients of measures of hedge funds exploiting stock anomalies is statistically significant. However, the coefficient of the *R-squared* is consistently negative and statistically significant, suggesting that investors tend to invest in hedge funds whose returns are less related to systematic risk factors. The coefficients of the interactions between measures of hedge funds exploiting anomalies and the crowdedness of such strategies are negative, however, they are not statistically significant either, except in Column (3) and in Column (6). The results

[9]Note that investors cannot know *ex ante* how crowded the hedge fund strategies are. Yet hedge fund performance may be affected by the crowdedness of their strategies. Media reports may provide some information to some degree.

appear to suggest that hedge fund investors do care about whether hedge funds deliver returns other than risk premiums but they care less about how such risk-adjusted performance is achieved.

## 2.6 Conclusions

In the past four decades, a number of firm characteristics have been found to be able to predict cross-sectional stock returns and cannot be explained by risk. This presents profitable opportunities for hedge funds who are viewed as prototypical arbitrageurs.

In this paper, using a sample of 3024 equity-oriented hedge funds, we investigate whether hedge funds exploit well-known stock market anomalies, and whether such exploitation activities can predict fund performance. We find that hedge funds on average have positive exposures to most of the anomalies used in this paper. Utilizing the dynamic conditional beta method and the Bayesian information criteria, we estimate time-varying hedge fund exposures to these anomalies and construct a measure for hedge funds' exploitation activities. We find that hedge funds that trade more aggressively on stock anomalies tend to earn higher alpha and higher appraisal ration in the subsequent 12 months. When hedge funds crowd into similar strategies or anomalies, more aggressive funds tend to earn lower alphas and appraisal ratio. Similarly, the effect of new funds' competition on hedge funds' performance also weakens the effectiveness of exploiting stock anomalies. The results are robust for alternative measures of hedge fund exploitation activities.

Investors may fear that funds that trade aggressively on stock anomalies might suffer negative skewness in the subsequent period, especially when many funds flock into the same strategies. We test whether hedge funds activities in trading stock anomalies have a negative impact on the skewness of fund returns. The panel regression shows that such activities in fact have a positive impact on the subsequent skewness of fund returns, but we also find that greater crowdedness tends to have an effect of reducing skewness for funds that trade more aggressively on stock anomalies. In contrast, funds whose R-squared is high when returns are regressed on Fama-French factors are more likely to suffer from more negative skewness.

Since funds that exploit stock anomalies more intensively tend to generate higher risk-adjusted returns, we examine whether investors appreciate these advantages and reward these hedge funds by investing more capital with them. We find that the measure of exploitation activities commands a coefficient that is not statistically significant. Crowdedness have a negative effect on flows to funds that exploit stock anomalies and the coefficient is not statistically significant either.

Taken together, our results show that hedge funds trade on stock market anomalies and get compensated by earning higher risk-adjusted returns. This provides supportive evidence for a few recent papers that find that hedge funds contribute to stabilize stock prices and enhance market efficiency.

# CHAPTER 3

# HEDGE FUND PERFORMANCE: UNIQUE STOCK HOLDINGS AND UNREPORTED ACTIONS

## 3.1 Introduction

Hedge funds are known for collecting management fees and performance fees. Various approaches have been proposed to assess whether hedge funds deserve the fees they charge. One way is to examine the overlaps or the uniqueness of the hedge fund holdings. After all, one should not pay high fees to hedge fund managers who simply mimic their peers' portfolios. Moreover, having large overlapping positions increases the risk of substantial losses in case of fire sales.

The stock-holdings data of institutional investors, especially mutual funds and hedge funds, have been used to analyze whether institutional investors exhibit stock-picking skills (e.g., Daniel et al. (1997) [31], Griffin and Xu (2009) [51]). Our analysis in this paper also relies on the use of holdings data of hedge funds. Specifically, we study the relationship between hedge fund performance and the uniqueness in hedge fund stock holdings and unreported actions.

We first study how unique hedge funds are in terms of their stock holdings and whether the uniqueness is positively associated with future performance of hedge funds. To do so, we need to have metrics to assess uniqueness. We employ four distance metrics as the measures of uniqueness in holdings. They are, namely, the portfolio independence, the Jaccard distance, the cosine distance, and the industry-level portfolio distance[1]. Sun et al. (2012) [74] propose a return-based measure for hedge fund distinctiveness and show that

[1] See their definitions in Section 3.

distinctive hedge funds tend to outperform those that are not distinctive. We sort hedge fund firms[2] into tercile groups based on the return-based uniqueness. If the distinctiveness results from uniqueness in stock holdings, then there should be a positive relationship between the two. The results show that hedge funds are very unique in terms of their holdings. For example, the level of portfolio independence is over 0.97 for all three groups of hedge funds, independent of the level of hedge fund distinctiveness. The other three uniqueness measures also indicate that the holdings of hedge funds are highly different. Even for a subsample of hedge funds whose reported returns are relatively closely correlated with holdings-based returns, the four measures of uniqueness are close among hedge funds. The results are consistent with Sias et al. (2014) [72] who also show hedge funds generally hold unique stocks in their portfolios.

We proceed to examine the relationship between uniqueness of stock holdings and hedge fund performance. Sorting the Fung and Hsieh (2004) seven-factor alpha on measures of hedge fund uniqueness, we find no evidence of hedge funds with unique stock holdings outperforming others. The results suggest that holding stocks that are not shared by peer hedge funds is not necessarily a sign of skills.

Hedge funds enjoy the flexibility of investing in assets and strategies other than long positions in stocks. Many of these investments are not disclosed. For example, hedge funds are not required to disclose their short positions in the Form 13F. We attempt to investigate whether these actions play an important role in the performance of hedge funds. To proxy for the unreported actions of hedge funds, we use one minus the R-squared of the regression of reported hedge fund returns on the holdings-based returns. We denote this variable as UDR. It has a positive correlation with Sun et al. (2012) distinctiveness and a negative correlation with Titman and Tiu (2011) R-squared.

[2] We use “hedge fund firms” and “hedge funds” interchangeably in this paper.

When we sort hedge funds into tercile portfolios based on UDR, we find that hedge fund alpha rise from 0.21 percent per month for the low-UDR hedge fund portfolio to 0.45 per month for the high-UDR hedge fund portfolio. The difference of the two is 0.24 percent per month, or 2.88 percent per year, which is both economically and statistically significant ($t$-statistic = 2.14). The average appraisal ratio also increases monotonically from the low-UDR hedge fund portfolio to the high-UDR. The non-annualized appraisal ratio for the low-UDR hedge fund portfolio is 0.05 and 0.25 for the high-UDR hedge fund portfolio. The difference is highly significant with a $t$-statistic of 6.84. The $t$-statistics are based on Newey and West (1987) [66] standard errors. The nonparametric results suggest that those unreported actions play an important role in predicting cross-section hedge fund performance.

We also investigate the predictive power of UDR for subsequent hedge fund performance in the Fama-MacBeth (1973, FM hereafter) regression setting where $t$-statistics are based on Newey and West (1987, NW hereafter) standard errors. The univariate regression results confirm the findings using the sorting approach that high-UDR hedge funds tend to outperform low-UDR funds, in terms of both [43] seven-factor alpha as well as appraisal ratio. When controlling for Sun et al. (2012) distinctiveness and Titman-Tiu (2011) R-squared, which also univariately predict hedge fund performance, as well as a set of fund characteristics, the coefficient of UDR becomes statistically insignificant, though it's still positive. For appraisal ratio, however, UDR retains its predictive power and are highly significant with t-statistics over 5. In contrast, the distinctiveness and the Titman-Tiu R-squared are no longer statistically significant when UDR is present. Based on these observations, we argue that unreported actions of hedge funds are important drivers of hedge fund performance.

Least squares estimation concentrates only on the conditional mean effect of covariates, whereas quantile regression provides a method for estimating the effect on different conditional quantiles of the response variable. We explore whether UDR has differing effect on different quantiles of hedge fund performance. For the seven-factor alpha, UDR has a significantly positive effect on lower quantiles. The effect declines as the quantile increases and becomes negative for the high quantiles of alpha, e.g., the 95th quantile. Combined with the results from the FM regression, the enhancement effect of UDR for hedge fund alpha is more notable for lower quantiles. As with the appraisal ratio, the coefficients of UDR for different quantiles vary around the least squares estimate in the FM regression, suggesting a strong effect of UDR enhancing the hedge fund appraisal ratios.

We extend the analysis to investigate how unreported actions of hedge funds are associated with hedge fund risk taking, liquidity, and return gap (Kacperczyk et al. (2008) [57]). We use the standard deviation of hedge fund returns as the measure of total portfolio risk of hedge funds. The FM regression results show that the coefficient of UDR is significantly negative when the standard deviation of hedge fund returns is the dependent variable. This finding indicates that hedge fund unreported actions help reduce the portfolio risk. The hedge fund literature has documented a positive serial correlation in hedge fund returns and suggested that it may be due to illiquid assets in the portfolios of hedge funds (e.g., Getmansky et al. (2004)). We explore how the serial correlation is associated with the level of UDR. Although the coefficient of UDR in the FM regression is positive, it is not statistically significant. We cannot conclude that the unreported actions of hedge funds lead to greater illiquidity in the portfolio of hedge funds, because the various assets that hedge funds can invest in, such as futures, may also be very liquid or increase the liquidity of hedge fund assets. The return gap, hedge fund reported returns minus holdings-based returns, measures the value added to or subtracted from stock investments. We find that UDR commands a significantly positive coefficient, suggesting that high-UDR hedge funds tend to exhibit high return gaps.

Our paper is related to Sias et al. (2014), who show that hedge fund stock holdings are highly unique. We confirm their findings, and in addition, we show that the uniqueness in stock holdings is not related to the performance of hedge funds. Our paper is also related to the work of Kacperczyk et al. (2008). They show that return gap of mutual funds is positively associated with mutual fund performance. We find that unreported actions of hedge funds, or UDR, have a positive impact on hedge fund performance. Besides, we find that opaque hedge funds (high-UDR) tend to exhibit high return gaps in the future, contrary to Kacperczyk et al.'s finding for mutual funds.

The rest of this paper is organized as follows. Section 2 describes the data used. Section 3 studies the relationship between the uniqueness in hedge fund stock holdings and hedge fund performance. Section 4 investigates whether unreported actions of hedge funds predict cross-section hedge fund performance. Section 5 concludes the paper.

## 3.2 Data

Our analysis relies on three data sources: hedge fund data from TASS and CISDM, holdings data from the 13F filings, and stock returns data from the CRSP.

We follow the procedures of Brunnermeier and Nagel (2004) [25], Griffin and Xu (2009) [51], and Cao et al. (2015) [27] to collect data for hedge funds. The first step of our data collection is to compile a list of the names of hedge fund firms from the TASS and the CISDM databases. We download 13F filings data from the Thomson Reuters. We then use firm names to match the institutional investors with the list of hedge fund firms. To ensure that we obtain as many hedge fund firms as possible, the matching requirement of firm names is mild. We then manually check the list to remove mismatches. For firms that are not perfectly matched in names, we check if they have the same address and resort to online resources to make sure that real matches are not excluded and spurious matches are deleted. Next, we check if the primary business of the matched firms is managing hedge funds. For firms that are registered with the SEC as investment advisors and file ADV forms, we manually check those SEC ADV forms and require those potential hedge fund firms to have more than 50% of their clients as high net worth individuals or more than 50% of investment is listed as "other pooled investment vehicles". Since charging performance fees is a feature of hedge funds, we also require that the investment advisor charges performance-based fees for their investment advisory services. After applying the above procedures, we obtain 446 hedge fund firms that filed 13F holdings data over the period of 1994 through the second quarter of 2014. Hedge fund firms often operate multiple hedge funds, and the hedge fund firms in our sample manage 1421 individual hedge funds.

Although hedge funds are relatively lightly regulated, hedge funds that manage over $100 million or more in 13F securities must file their quarterly holdings on the Form 13F with the SEC. Equity positions worth more than $200,000 or consisting of more than 10,000 shares must be reported. We carefully merge the stock holdings data with the monthly stock returns data from the CRSP.

## 3.3 Holdings-based Uniqueness and Hedge Fund Performance

In this section, we discuss the uniqueness in hedge fund stock holdings and examine its relationship with hedge fund performance. We adopt four measures to assess the overlapping or the uniqueness in hedge fund stock holdings. For each measure, we compute it for every pair of hedge funds in a given quarter, and the average of that measure for fund *i* with all other hedge funds is considered the uniqueness measure for fund *i* in that quarter.

We begin with a metric that is similar to the Active Share proposed by Cremers and Petajisto (2009) [30] and modified and used in Sias et al. (2014), who term it as *portfolio independence* (PI). It equals one half of the absolute difference in two hedge fund firms' stock position weights (See Equation (3.1)).

$$PI_{i,j,t} = \frac{1}{2}\sum_{k=1}^{K} |w_{i,k,t} - w_{j,k,t}| \tag{3.1}$$

where *i* and *j* denote hedge funds and *k* denotes stocks in quarter *t*. If two hedge funds have no stocks in common in their holdings, then $PI_{i,j,t}$ equals one. If two funds have the same portfolio holdings, then $PI_{i,j,t}$ equals zero. Less than perfect overlapping would yield a value between zero and one for PI.

The second measure of uniqueness in stock holdings, *Jaccard Distance* (JD), simply calculates the proportion of non-overlapped stock positions in a pair of hedge funds (See Equation (3.2)). This metric also has a possible range from zero to one, with one indicating no overlapping in two portfolios.

$$JD_{i,j,t} = 1 - \frac{\#STK_{i,j,t}}{\#STK_{i,t} + \#STK_{i,t} - \#STK_{i,j,t}} \tag{3.2}$$

Sias et al. (2014) argue that the overlap contribution of a stock to the portfolio independence measure is determined by the smaller portfolio weight. However, the cosine similarity does not have this limitation because it focuses on the product of the overlapping portfolio weights. Thus, our third measure for the uniqueness of hedge fund stock holdings is the *cosine distance* (CDS) given in Equation (3.3).

$$CDS_{i,j,t} = 1 - \frac{\sum_{k=1}^{K} w_{i,k,t} w_{j,k,t}}{\sqrt{\sum_{k=1}^{K} w_{i,k,t}^2}\sqrt{\sum_{k=1}^{K} w_{j,k,t}^2}} \tag{3.3}$$

The previous three metrics compare stock portfolio weights at the stock level. Managers could have expertise in some particular industries (Kacperczyk et al. (2005) [56]), so they may focus on industry-level information and share more common investments in terms of industries invested in. Our fourth measure of uniqueness in hedge fund stock holdings calculates portfolio independence at the *industry* level. The subscript *l* in Equation (3.4) denotes industry *l*.

$$IPI_{i,j,t} = \frac{1}{2}\sum_{l=1}^{L} |w_{i,l,t} - w_{j,l,t}| \tag{3.4}$$

Sun et al. (2012) argue that a hedge fund needs to be distinct from its peers if it desires to earn abnormal returns persistently in the highly competitive industry. They assess the distinctiveness of a fund using the correlation between the fund's return and the returns of hedge funds employing similar strategies. Specifically, the *distinctiveness* of a hedge fund is calculated as in Equation (3.5).

$$DISTINCT_i = 1 - Corr(R_i, \mu_I) \tag{3.5}$$

where $\mu_I$ is the average return of hedge funds of the same style.

We sort holdings-based uniqueness measures into tercile groups on the return-based uniqueness. Our first measure of holdings-based uniqueness – portfolio independence – exhibits a very high level of uniqueness of hedge fund holdings. According to Equation (3.1), larger values of PI indicate greater uniqueness and the maximum of PI is 1. In Panel A Table 22, portfolio 1 includes hedge funds that are the least distinctive from an average hedge fund in terms of the correlation of hedge fund returns. However, the equity holdings of this group of hedge funds are actually very unique, with the value of PI being 0.9713, which is very close to 1. Similarly, the PI of portfolio 2 and portfolio 3 are also over 0.97. The difference of the PI is not statistically significant. The results are consistent with the findings of Sias et al. (2014). The Jaccard distance simply measures the overlapping in hedge fund holdings. Like the portfolio independence, the maximum value of the Jaccard distance is 1 and higher values indicate greater uniqueness. We find that the Jaccard distance is also close to 1 for each of the three groups of hedge funds, with each Jaccard distance exceeding 0.98. Sias et al. (2014) argue that the overlap contribution from any stock to the portfolio independence is the minimum of the smaller portfolio weight, whereas, the cosine distance does not have such limitation. In column (3), it shows that the cosine distance is also consistently high among the three groups of hedge funds, corroborating the findings for the portfolio independence and the Jaccard distance. The column (4) presents the sorting of industry-level portfolio independence. Although the industry-level portfolio independence increases from portfolio 1 to portfolio 3 and the difference between portfolio 1 and portfolio 3 is statistically significant, they are actually very close across the three portfolios. Thus, the full sample shows that hedge funds seem to be quite unique in terms of their long equity positions.

In Panel B Table 22, we study a subsample of hedge funds, the returns of which are relatively more correlated with a series of returns derived from stock holdings. Specifically, we pick a threshold of 0.5. We construct the holdings-based return series by assuming that hedge funds hold the quarter *t-1* disclosed stock holdings in quarter *t* and using those weights to calculate monthly returns of the stock portfolio for quarter *t*. Using this subsample, we also sort the holdings-based uniqueness measures on the return-based distinctiveness. It shows that in this subsample, all uniqueness measures increases with respect to hedge fund distinctiveness. The difference between portfolio 3 and portfolio 1 is statistically significant for all the four uniqueness measures, though all three portfolios exhibit high level of uniqueness in their equity holdings. Hence, both Panel A and Panel B of Table 22 reveal that hedge funds tend to be quite unique in that they share a rather small overlap in their equity holdings.

We proceed to study whether hedge fund performance is associated with hedge fund distinctiveness and uniqueness in equity holdings. The hedge fund performance metric used here is the Fung and Hsieh (2004) seven-factor alpha. In Table 23, we sort hedge funds into tercile groups based on the return-based distinctiveness and the four holdings-based uniqueness measures, and then we calculate the average alpha of each group in the subsequent 12 months.

We first examine the relationship between hedge fund uniqueness and performance using the full sample (Panel A Table 23). In column (1), hedge funds are sorted on the return-based hedge fund distinctiveness, and portfolio 1 includes the least distinctive hedge funds while portfolio 3 includes the most distinctive ones. Consistent with Sun et al. (2012), we find that funds that are more distinct from others tend to outperform. The least distinctive funds earn 0.22 percent of alpha per month, whereas the most distinctive funds earn 0.49 percent per month. The difference of the two, 0.27 percent per month, is statistically significant ($t$-statistic = 4.13). The next four columns are for the holdings-based uniqueness measures. However, we do not observe a significantly positive association between hedge fund performance and holdings-based uniqueness. For hedge funds that have the lowest level of portfolio independence, the monthly average alpha is 0.36 percent. Nonetheless, for hedge funds that have the highest level of portfolio independence, the monthly average alpha is 0.25 percent. The underperformance of funds with high portfolio independence is statistically significant ($t$-statistic = -2.81). For the rest of the three holdings-based uniqueness measures, there is no significant and positive association with hedge fund alpha, either.

Panel A Table 23 suggests that uniqueness in equity holdings does not lead to superior hedge fund performance. The lack of evidence that uniqueness in equity holdings contribute to hedge fund performance might be due to low correlation between reported returns and holdings-based returns. Therefore, in Panel B Table 23, we focus on the subsample with high correlation between the two return series, as in Panel B Table 22.

We find that, in the subsample, distinctiveness is still positively associated with hedge fund performance. The gap between the alpha of less distinctive funds and that of more distinctive funds actually becomes even wider. However, portfolio independence is still negatively associated with the alpha of hedge funds, though the underperformance of high-PI hedge funds is not statistically significant. Even in this subsample, holdings-based uniqueness does not exhibit a positive relation with hedge fund performance. Table 22 and Table 23 suggest that hedge funds are quite unique in their equity holdings and such uniqueness does not predict cross-section hedge fund performance.

To further study the relation between uniqueness in hedge fund equity holdings and performance, we apply the method of Sun et al. (2012) to the holdings-based return series and compute the holdings-based distinctiveness (HDIST). We sort HDIST on the return-based distinctiveness (Panel A Table 24) and then sort hedge fund performance on HDIST (Panel B Table 24). Unlike the previous holdings-based measures of uniqueness, HDIST increases monotonically from hedge fund portfolio 1 to portfolio 3 with respect to the return-based distinctiveness. The difference of HDIST between portfolio 3 and portfolio 1 is statistically significant. Thus the two measures of distinctiveness are positively related. Then we examine how HDIST interacts with hedge fund performance. Yet HDIST still does not exhibit positive relation with hedge fund performance. Table 24 confirms that uniqueness in hedge fund holdings does not lead to superior hedge fund performance.

## 3.4 Unobserved Actions and Hedge Fund Performance

In addition to the long positions in equities, hedge funds may invest in various kinds of assets and strategies, for example, derivatives. Although some hedge funds selectively disclose their positions in options, most positions in derivatives are not known to the public. Hedge funds are also major players in shorting stocks, but they are not required to report their short positions. In this section, we attempt to investigate how the unobserved actions of hedge funds are associated with hedge fund performance.

To this end, we need a proxy for the unobserved actions of hedge funds. We deal with this issue by using the R-squared from regressing reported hedge fund returns on the return series based on the stock holdings weights. Specifically, we estimate the following regression each month using data from past twelve months:

$$R_t = a + bR_t^H + \epsilon_t. \tag{3.6}$$

The $R_t$ in Equation (3.6) is the reported return of a hedge fund firm[3] and $R_t^H$ is the holdings-based return. Then we calculate our measure for the role of unobserved actions as a driver of hedge fund returns using Equation (3.7).

$$UDR = 1 - R^2 \tag{3.7}$$

[3]We use equal-weighted average of returns for funds within a firm. Results using value-weighted returns by AUM are similar.

where $R^2$ is the adjusted R-squared obtained from regression (3.6). If unreported actions are (not) the main driver of returns of a hedge fund, then UDR would be high (low). Our primary interest is to study whether UDR can predict future hedge fund performance.

Before that, we first explore the characteristics of high-UDR funds. Table 25 reports summary statistics for hedge fund company-level characteristics for three groups of hedge funds sorted on UDR. The first column shows that high UDR hedge funds are, on average larger than low UDR ones ($150.59 million versus $99.53 million). Column (2) indicates that high UDR hedge funds tend to be younger. The next two columns show that the mean difference between high and low UDR hedge funds in performance fees is -0.66% and the mean difference in management fee is 0.12%. The last two characteristics are for share restrictions. High UDR hedge funds tend to have shorter lockup period than the low UDR funds, and the mean difference is about 0.8 month. The mean difference in redemption notice period is not significantly different between the two groups.

In Table 26, we report the correlation matrix among hedge fund performance metrics and variables that potentially measure hedge fund manager skills. Performance metrics used are the Fung and Hsieh (2004) seven-factor alpha and the appraisal ratio in the future 12 months. Our main variable of interest is UDR, which is one minus the R-squared of regressing hedge fund reported returns on holdings-based returns. The other three variables are, return-based hedge fund distinctiveness, the Titman-Tiu (2011) R-squared based on the Fung and Hsieh (2004) seven-factor model, and the return gap proposed by Kacperczyk et al. (2008) and computed as the reported hedge fund returns minus the holdings-based returns.

The upper triangle of Table 26 presents the Pearson correlation coefficient and the lower triangle shows the Spearman correlation coefficient. The boldness of the numbers indicates that the correlation coefficient is significant at the 5% significance level.

Table 26 shows that both the Pearson correlation coefficient and the Spearman correlation coefficient between UDR and the future performance metrics are significantly positive.

For example, the Spearman correlation coefficient for UDR and future alpha is 0.1246 and it is 0.1878 for UDR and future appraisal ratio. This suggests that unobserved actions of hedge funds may benefit hedge fund performance. In addition, UDR is fairly closely related to the distinctiveness of hedge funds. This makes sense because hedge funds that are less focusing on equities are more likely to be distinctive in that their returns are less correlated. UDR is even more correlated with the Titman-Tiu (2011) R-squared. Both the Pearson correlation coefficient and the Spearman correlation coefficient is as high as about -0.7. This suggests that hedge funds that engage more heavily in activities other than long equity positions also tend to rely less on systematic risks, which would enable the hedge funds to create value for investors. The relatively high correlation between UDR and distinctiveness and the Titman-Tiu (2011) R-squared necessitates further examination of the incremental predictive power of UDR for future hedge fund performance. In addition, UDR is not highly correlated with the return gap.

Hedge fund performance metrics are significantly correlated with the distinctiveness, the Titman-Tiu (2011) R-squared, and the return gap, and the signs are consistent with previous findings.

Next, we focus on the relationship between UDR and hedge fund performance. We sort hedge funds into tercile groups according to UDR. Then we compute the average alpha and the appraisal ratio in the subsequent 12 months for each group of hedge funds. Results are shown in Table 27.

Portfolio 1 includes hedge funds with the lowest UDR each month. The average alpha is 0.21 percent per month. The average alpha increases to 0.33 percent per month for hedge funds in portfolio 2 and to 0.45 percent for hedge funds in portfolio 3. This confirms the positive relation between UDR and hedge fund alpha. The difference of alpha for hedge fund portfolio 3 and portfolio 1 is about 0.24 percent per month, which is 2.88 percent per annum, with NW adjusted *t*-statistic of 2.14. Hence, the difference of alpha is economically and statistically significant. For appraisal ratio, there is also a monotonically increasing pattern from low UDR hedge funds to high UDR hedge funds. The average monthly appraisal ratio for hedge funds in portfolio 1 is 0.0459, while it is 0.2460 for hedge funds in portfolio 3. The difference between the two is 0.2 and the associated NW adjusted $t$-statistic is 6.84. Table 27 suggests that hedge fund activities other than long equity investments are positively associated with hedge fund performance, suggesting that this type of activities create value for investors.

The nonparametric method–portfolio sorting–shows that UDR is positively associated with future hedge fund performance. We then study the predictive power of UDR for hedge fund performance in the regression analysis setting. We employ the Fama and MacBeth (1973) regression. Each month we regress the future hedge fund performance on UDR and other control variables, and then we take the average of the coefficients and calculate the standard errors by adjusting heteroscedasticity and autocorrelation using the NW procedure.

Panel A Table 28 contains regression results with hedge fund future alphas being the dependent variable. Column (1) is for the univariate regression in which the UDR is the only explanatory variable. The coefficient of UDR is 0.0034 and the $t$-statistic based on the NW standard errors is 2.26, corroborating the findings by portfolio sorting. An increment of one standard deviation of UDR leads to an increment of 45 basis points of alpha in the subsequent 12 months. Column (2) and column (3) show that distinctiveness of hedge funds and the Titman-Tiu (2011) R-squared also command statistically significant coefficients in univariate regressions, and the signs of the coefficients are consistent with previous findings. In these three regressions, the one using UDR as the independent variable has the highest R-squared. In column (4) we include the three explanatory variables in the regression. It turns out that all the three coefficients decreased by one half, compared with the coefficients in the univariate regressions. None of the three coefficients are statistically significant. The results in column (5) are similar when we add fund characteristics.

This may result from the relatively high correlation between the three variables. They all, to some extent, measure how distinct hedge funds are from each other.

We further study the predictive power of these variables for future hedge fund appraisal ratios. Results are presented in Panel B Table 28. The first three columns are for univariate regressions. All three variables are statistically significant in univariate regressions. The coefficient of UDR is 0.2689 and the *t*-statistic is 6.47. Consistent with the nonparametric portfolio sorting results, the univariate regression shows that UDR positively predicts future hedge fund appraisal ratios. Column (2) and column (3) suggest that hedge funds that are more distinctive and rely less on systematic risks also tend to earn higher appraisal ratio. Like in Panel A Table 28, we also study their marginal predictive power controlling for each other and fund characteristics. In these two multivariate regressions where the future appraisal ratio is the dependent variable, UDR retains its predictive power. The magnitude of the coefficient remains similar, and the associated *t*-statistic also does not change significantly. On the contrary, the coefficient of distinctiveness changes signs and becomes statistically insignificant. Although the coefficient of the Titman-Tiu (2011) R-squared is still negative, it is no longer significantly distinguishable from 0.

Table 28 suggests that UDR, which measures the reliance of hedge funds on activities other than long equity investments, such as short selling and derivatives, is beneficial for hedge fund future performance, especially the appraisal ratio. Perhaps these areas are not as competitive as the long equity investments and thus there are more opportunities to create value for investors.

In Table 28, we examined the relation between UDR and hedge fund future performance, using least squares models. Least squares models summarize how explanatory variables influence the conditional mean of the response variable. This average relationship is assumed to be constant throughout the conditional distribution of the outcome variable. However, this sometimes could be misleading if the constant relationship does not hold across the conditional distribution. In contrast, the quantile regression can provide a more detailed view of how regressors impact on the different points in the conditional distribution of the response variable. In addition, the quantile regression is robust to outliers which can notoriously affect the estimates of the least squares models.

We explore the relationship between hedge fund performance and UDR as well as other control variables at a set of quantiles in the conditional distribution of fund performance. We select the 5th, 25th, 50th, 75th, and the 95th percentile in the conditional distribution of hedge fund performance. Results are reported in Table 29. The *t*-statistics in the parentheses are based on Bootstrap standard errors with 200 repetitions.

Panel A Table 29 presents the results for hedge fund alphas. Column (1) shows how the set of explanatory variables impact on the 5th percentile of the conditional distribution of alpha. Our main variable of interest is the UDR. The coefficient of UDR is 0.0128 and its *t*-statistic is 8.69, indicating a strong enhancing effect of UDR on the left tail of the distribution of alpha. As we move to higher quantiles, we find that the coefficient of UDR declines monotonically. At the 25th percentile, the coefficient of UDR is 0.0071, while at the 75th percentile it is 0.001. More strikingly, at the right tail of the distribution, UDR even commands a negative coefficient (-0.0061) and it is statistically significant (*t*-statistic = -5.15). Although the mean effect of UDR on hedge fund future alpha is not statistically significant, there is notable and positive effect on some quantiles of future alpha, especially at the lower quantiles.

We also conduct quantile regressions for the appraisal ratio of hedge funds at the aforementioned quantiles. At all these five quantiles of the distribution of hedge fund appraisal ratio, the coefficient of UDR is positive and statistically significant. The magnitude of the coefficient at the tails is larger than that in the interior quantiles. However, they are around the mean effect shown in Table 28. Therefore, the quantile regression results and the FM regression results show a robust relationship between UDR and hedge fund appraisal ratio, suggesting that short selling and other activities of hedge funds can enhance subsequent hedge fund performance.

Next, we explore the impact of hedge funds' involvement in short selling and other activities on hedge fund risk taking, liquidity, and return gap.

We first investigate how UDR is associated with the level of total risk that hedge funds take. Total risk is calculated as the standard deviation of hedge fund returns in the subsequent 12 months. Hedge funds enjoy the flexibility of using various kinds of instruments to manage their portfolios. Derivatives are certainly an important tool for hedge funds. Aragon and Martin (2012) find that hedge funds that use options in their portfolios generate lower risk than options nonusers. We formally test the relationship between UDR and hedge fund total risk by estimating the following FM regression with future total risk as the dependent variable.

$$TotRisk = a + bUDR + cControl + \epsilon \tag{3.8}$$

The variable of our primary interest is UDR. Column (1) Table 30 shows that the coefficient of UDR is negative and statistically significant ($t$-statistic = -9.80). The results indicate that hedge funds with more unreported activities, such as short selling and derivative investment, tend to exhibit less risk, which is consistent with Aragon and Martin's (2012) finding.

Hedge funds often invest in illiquid assets in order to exploit inefficiencies. This tends to lead to positive serial correlation in hedge fund returns. We examine whether unreported activities of hedge funds are related to investments in illiquid assets by estimating regression (3.8) with the first-order serial autocorrelation of hedge fund returns as the dependent variable. Results are shown in the column (2) Table 30. The coefficient of UDR is positive yet not statistically significant, indicating that unreported positions of hedge funds do not necessarily lead to illiquidity in hedge fund assets.

Finally, we investigate the relationship between UDR and the subsequent return gap. Return gap is computed as the reported hedge fund returns minus the holdings-based returns. High return gap would suggest additional value created from actions other than investing in long equity positions. High UDR indicates that hedge fund involves in more unreported actions and is more opaque. Whether opaque hedge funds exhibit good or poor return gap is an empirical question.

Using the average return gap in the subsequent 12 months as the dependent variable, we estimate the regression (3.8) and focus our interest on the coefficient on UDR. We also control for the past return gap.

Results in the column (3) Table 30 show that the coefficient of UDR is positive (0.0035) and statistically significant ($t$-statistic = 3.28) and suggest that opaque hedge funds tend to exhibit superior return gaps. This is at odds with findings for mutual funds. Kacperczyk et al. (2008) find that opaque mutual funds are associated with poor return gaps.

## 3.5 Conclusion

In this paper, we explore the role of hedge fund uniqueness of equity long positions as well as the role of unreported actions of hedge funds in predicting hedge fund performance.

Using the holdings of 446 hedge fund firms obtained from Form 13F disclosures, we construct four measures of uniqueness of hedge fund equity holdings. Then we study their relationship with hedge fund performance. However, we find no evidence of uniqueness of hedge fund equity holdings driving the performance of hedge funds.

Hedge funds are lightly regulated and can invest in various kinds of assets and strategies. These investments are often not disclosed to the public. We study whether these actions enhance hedge fund performance. To gauge the importance of unreported actions for hedge funds, we use one minus the R-squared of the regression of reported hedge fund returns on holdings-based hedge fund returns. We denote this variable as UDR. We find that hedge funds with high UDR tend to be associated with higher subsequent alphas, especially in the lower tails of the distribution of alphas. These funds also tend to exhibit superior appraisal ratios. We then investigate the relationship between UDR and risk taking of hedge funds. Our results show that hedge funds with high UDR exhibit lower standard deviations, indicating that those unreported actions help reduce the total risk of the portfolios of hedge funds. Lastly, we show that hedge funds with high UDR tend to exhibit higher return gaps in the subsequent months.

**Table 1.** Summary Statistics of Fund Characteristics and Performance

This table provides descriptive statistics for hedge fund characteristics and monthly net-of-fee returns. Fund characteristics include age (number of observations divided by 12), most recent fund size in $M, a dummy variable with 1 denoting offshore vehicle, redemption notice period (days), lockup period (months), management fee, performance fee, whether or not using high water mark, and lastly, whether or not using leverage. Panel A and Panel B are for live funds and defunct funds, respectively. Panel C presents the average monthly return, the standard deviation, the median, the first quartile, the third quartile, the fifth and the ninety-fifth percentile, average Sharpe ratio, and skewness as well as kurtosis of returns. Note these numbers are computed after correcting the autocorrelation in the original monthly returns. The last row of Panel C shows the average autocorrelation of hedge fund monthly returns before de-smoothing.

| Panel A: Live Fund Characteristics | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | Age | Size | Offshore | Notice | Lockup | MFee | PFee | HW | Leveraged |
| Mean | 11.07 | 217.48 | 0.47 | 44.23 | 4.67 | 1.45 | 15.40 | 0.78 | 0.61 |
| SD | 4.74 | 620.88 | 0.50 | 33.36 | 7.77 | 0.53 | 7.59 | 0.42 | 0.49 |
| 5th Pctl | 4.67 | 3.25 | 0.00 | 0.00 | 0.00 | 0.65 | 0.00 | 0.00 | 0.00 |
| 25th Pctl | 7.25 | 19.00 | 0.00 | 30.00 | 0.00 | 1.00 | 10.00 | 1.00 | 0.00 |
| Median | 10.17 | 53.58 | 0.00 | 31.00 | 0.00 | 1.50 | 20.00 | 1.00 | 1.00 |
| 75th Pctl | 14.33 | 164.04 | 1.00 | 60.00 | 12.00 | 2.00 | 20.00 | 1.00 | 1.00 |
| 95th Pctl | 20.00 | 888.00 | 1.00 | 95.00 | 12.00 | 2.00 | 20.00 | 1.00 | 1.00 |
| Panel B: Defunct Fund Characteristics | | | | | | | | | |
| | Age | Size | Offshore | Notice | Lockup | MFee | PFee | HW | Leveraged |
| Mean | 8.36 | 155.23 | 0.53 | 41.41 | 4.12 | 1.42 | 15.95 | 0.71 | 0.60 |
| SD | 3.59 | 507.98 | 0.49 | 29.91 | 6.80 | 0.71 | 7.32 | 0.45 | 0.49 |
| 5th Pctl | 4.25 | 1.92 | 0.00 | 0.00 | 0.00 | 0.62 | 0.00 | 0.00 | 0.00 |
| 25th Pctl | 5.50 | 11.17 | 0.00 | 30.00 | 0.00 | 1.00 | 10.00 | 0.00 | 0.00 |
| Median | 7.33 | 32.45 | 1.00 | 30.00 | 0.00 | 1.50 | 20.00 | 1.00 | 1.00 |
| 75th Pctl | 10.58 | 103.60 | 1.00 | 60.00 | 12.00 | 1.75 | 20.00 | 1.00 | 1.00 |
| 95th Pctl | 15.50 | 636.00 | 1.00 | 90.00 | 12.00 | 2.00 | 20.00 | 1.00 | 1.00 |

Panel C: Hedge Fund Returns

| | All | Directional Traders | Funds of Funds | Multiprocess | Others | Relative Value | Security Selection |
|---|---|---|---|---|---|---|---|
| Mean | 0.0074 | 0.0089 | 0.0050 | 0.0078 | 0.0087 | 0.0063 | 0.0088 |
| SD | 0.0597 | 0.0739 | 0.0395 | 0.0462 | 0.0569 | 0.0405 | 0.0737 |
| 5th Pctl | -0.0663 | -0.0925 | -0.0475 | -0.0526 | -0.0497 | -0.0401 | -0.0765 |
| 25th Pctl | -0.0100 | -0.0189 | -0.0074 | -0.0057 | -0.0036 | -0.0043 | -0.0135 |
| Median | 0.0069 | 0.0064 | 0.0064 | 0.0076 | 0.0071 | 0.0065 | 0.0077 |
| 75th Pctl | 0.0246 | 0.0351 | 0.0197 | 0.0223 | 0.0204 | 0.0180 | 0.0305 |
| 95th Pctl | 0.0812 | 0.1160 | 0.0515 | 0.0664 | 0.0683 | 0.0540 | 0.0947 |
| SR | 0.2175 | 0.1722 | 0.1886 | 0.2750 | 0.3562 | 0.3072 | 0.2151 |
| Skew | -0.3017 | 0.0880 | -0.7194 | -0.3851 | -0.1107 | -0.7958 | 0.0156 |
| Kurt | 5.2341 | 4.2032 | 5.1967 | 6.3307 | 5.6500 | 9.9926 | 4.0297 |
| $\rho_1$ before de-smoothing | 0.1981 | 0.1429 | 0.2445 | 0.2215 | 0.1772 | 0.2129 | 0.1774 |

**Table 2.** Summary Statistics of Hedge Fund Activeness

This table reports summary statistics for the cross section of hedge fund activeness. Hedge funds are grouped into six investment styles according to the method of MorningStar and Agarwal et al. (2009).

| Style | Mean | Std. | 25th Percentile | 50th Percentile | 75th Percentile |
|---|---|---|---|---|---|
| Directional Traders | 0.8085 | 1.1761 | 0.2276 | 0.5154 | 0.9879 |
| Funds of Funds | 0.4295 | 0.5151 | 0.1901 | 0.3147 | 0.5054 |
| Multiprocess | 0.5031 | 0.9015 | 0.1647 | 0.3082 | 0.5961 |
| Others | 0.4680 | 0.6301 | 0.1305 | 0.2637 | 0.5629 |
| Relative Value | 0.4215 | 0.7503 | 0.1291 | 0.2508 | 0.4799 |
| Security Selection | 0.7516 | 1.3581 | 0.2265 | 0.4298 | 0.7495 |

**Table 3.** Persistence of Hedge Fund Activeness

This table reports summary statistics for the persistence of hedge fund activeness. Hedge funds are allocated into quintile portfolios each month according to their activeness in the past twelve months. Then the activeness for the subsequent three months, six months, and twelve months are calculated. Panel A reports equally-weighted average activeness for each quintile portfolio of hedge funds, while Panel B reports value-weighted means.

| Panel A: Equally-weighted Hedge Fund Portfolio Activeness | | | | |
|---|---|---|---|---|
| | | Subsequent | | |
| Portfolio | Past 12M | 3M | 6M | 12M |
| Q1 | 0.0691 | 0.1185 | 0.1254 | 0.1343 |
| 2 | 0.1820 | 0.2428 | 0.2520 | 0.2600 |
| 3 | 0.3193 | 0.3682 | 0.3724 | 0.3767 |
| 4 | 0.5467 | 0.5651 | 0.5673 | 0.5681 |
| Q5 | 1.5920 | 1.3345 | 1.3148 | 1.2904 |
| Q5 - Q1 | 1.5229 | 1.2160 | 1.1894 | 1.1561 |
| *t*-statistic | (22.98) | (24.34) | (22.64) | (20.92) |
| Panel B: Value-weighted Hedge Fund Portfolio Activeness | | | | |
| Q1 | 0.0696 | 0.1190 | 0.1295 | 0.1404 |
| 2 | 0.1819 | 0.2393 | 0.2482 | 0.2570 |
| 3 | 0.3185 | 0.3546 | 0.3549 | 0.3565 |
| 4 | 0.5442 | 0.5432 | 0.5415 | 0.5406 |
| Q5 | 1.4049 | 1.1772 | 1.1486 | 1.1081 |
| Q5 - Q1 | 1.3353 | 1.0583 | 1.0190 | 0.9677 |
| *t*-statistic | (20.93) | (23.80) | (24.10) | (25.54) |

## **Table 4.** Determinants of Hedge Fund Activeness

This table presents panel data regression results for explaining hedge fund activeness. The dependent variable is the activeness of individual hedge funds over the subsequent 12 months. The independent variables include activeness in the past 12 months ($\text{ACT}_{t-11:t}$), cumulative returns in the past 12 months ($\text{CUMRET}_{t-11:t}$), return volatility in the past 12 months ($\text{VOL}_{t-11:t}$), average flow in the past 12 months ($\text{FLOW}_{t-11:t}$), the natural logarithm of fund size (LOGSIZE), the fund age, the management fee (MFEE), the performance fee (PFEE), the lockup months (LOCKUP), the redemption notice period in 30 days (NOTICE), and an indicator of whether the fund being offshore (OFFSHORE), HW is a dummy variable with 1 denoting high water mark being used. In columns (2) and (4) we substitute percentile rank of cumulative returns ($\text{PCTLRNK}_{t-11:t}$) for past cumulative returns. Numbers in the parentheses are $t$-statistics which are adjusted for fund-clustering effect, and time and cluster-style fixed effects. $^{***}$, $^{**}$ and $^{*}$ denote significance at the level of 1%, 5%, and 10%, respectively.

| | *Dependent variable:* $ACT_{t+1:t+12}$ | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| $\text{ACT}_{t-11:t}$ | 0.6524*** | 0.6940*** | 0.6525*** | 0.6940*** |
| | (71.89) | (65.52) | (72.08) | (65.61) |
| $\text{CUMRET}_{t-11:t}$ | −0.0389*** | | −0.1234* | |
| | (−5.56) | | (−1.93) | |
| $\text{PCTLRNK}_{t-11:t}$ | | −0.0268*** | | −0.0903** |
| | | (−6.92) | | (−2.07) |
| $\text{VOL}_{t-11:t}$ | 0.1163 | 0.2219** | 0.1128 | 0.2219** |
| | (1.08) | (1.97) | (1.07) | (1.97) |
| $\text{RHO}_{t-11:t}$ | 0.0171*** | 0.0182*** | 0.0175*** | 0.0186*** |
| | (5.49) | (5.68) | (5.62) | (5.82) |
| $\text{FLOW}_{t-11:t}$ | −0.0392** | −0.0347** | −0.0389** | −0.0330** |
| | (−2.54) | (−2.13) | (−2.53) | (−2.03) |
| LOGSIZE | −0.0018** | −0.0022*** | −0.0027*** | −0.0049*** |
| | (−2.26) | (−2.83) | (−3.11) | (−3.26) |
| AGE | −0.0033*** | −0.0032*** | −0.0033*** | −0.0035*** |
| | (−10.63) | (−10.96) | (−9.72) | (−6.53) |
| LOCKUP | 0.0005** | 0.0004** | 0.0004* | −0.0001 |
| | (2.57) | (2.10) | (1.86) | (−0.31) |
| NOTICE | −0.0022* | −0.0018 | −0.0028* | −0.0036 |
| | (−1.69) | (−1.41) | (−1.96) | (−1.46) |
| MFEE | 0.2788 | 0.2175 | 0.4326* | 0.5150 |
| | (1.28) | (1.04) | (1.69) | (1.29) |
| PFEE | 0.0337* | 0.0536** | 0.0507** | 0.1200*** |
| | (1.88) | (2.36) | (2.53) | (3.02) |
| OFFSHORE | −0.0029 | −0.0024 | −0.0033 | −0.0042 |
| | (−1.18) | (−1.02) | (−1.21) | (−0.90) |
| HW | −0.0030 | −0.0039 | −0.0020 | −0.0003 |
| | (−0.98) | (−1.34) | (−0.59) | (−0.06) |
| $\text{CUMRET}_{t-11:t}/\text{PCTLRNK}_{t-11:t}$∗LOGSIZE | | | 0.0082** | 0.0053** |
| | | | (2.28) | (2.22) |
| $\text{CUMRET}_{t-11:t}/\text{PCTLRNK}_{t-11:t}$∗AGE | | | −0.0002 | 0.0006 |
| | | | (−0.16) | (0.71) |
| $\text{CUMRET}_{t-11:t}/\text{PCTLRNK}_{t-11:t}$∗LOCKUP | | | 0.0009 | 0.0010* |
| | | | (1.15) | (1.73) |
| $\text{CUMRET}_{t-11:t}/\text{PCTLRNK}_{t-11:t}$∗NOTICE | | | 0.0053 | 0.0035 |
| | | | (0.87) | (0.84) |
| $\text{CUMRET}_{t-11:t}/\text{PCTLRNK}_{t-11:t}$∗MFEE | | | −1.5288* | −0.6237 |
| | | | (−1.78) | (−1.05) |
| $\text{CUMRET}_{t-11:t}/\text{PCTLRNK}_{t-11:t}$∗PFEE | | | −0.1736* | −0.1372** |
| | | | (−1.82) | (−2.32) |
| $\text{CUMRET}_{t-11:t}/\text{PCTLRNK}_{t-11:t}$∗OFFSHORE | | | 0.0042 | 0.0035 |
| | | | (0.36) | (0.46) |
| $\text{CUMRET}_{t-11:t}/\text{PCTLRNK}_{t-11:t}$∗HW | | | −0.0081 | −0.0063 |
| | | | (−0.52) | (−0.68) |
| Adj. $R^2$ | 54.25 | 54.87 | 54.29 | 54.90 |

**Table 5.** Portfolio Performance Sorted on Past Activeness

This table presents average performance measures for portfolios sorted according to past 12-month activeness. Quintile portfolio 1 contains the least active funds in each month whereas quintile portfolio 5 contains the most active funds each month. Performance measures are computed using subsequent 12 observations each month. $\alpha$ is calculated as the average of monthly abnormal returns. $AR$ is the appraisal ratio calculated as alpha divided by the standard deviation of monthly abnormal returns. $SR$ is the Sharpe ratio. $MPPM3$ is the manipulation-proof performance measure. Numbers in the parentheses are $t$-statistics based on Newey-West standard errors.

| Quintile | $\alpha$ | AR | SR | MPPM3 |
|---|---|---|---|---|
| Q1 | 0.0047 | 0.4437 | 0.4504 | 0.0249 |
| 2 | 0.0049 | 0.3077 | 0.3708 | 0.0286 |
| 3 | 0.0049 | 0.2403 | 0.3174 | 0.0263 |
| 4 | 0.0053 | 0.1982 | 0.2255 | 0.0195 |
| Q5 | 0.0066 | 0.1615 | 0.2255 | -0.0191 |
| Diff. | 0.0019 | -0.2822 | -0.2249 | -0.0440 |
| $t$-statistic | (1.72) | (-9.18) | (-7.30) | (-2.22) |

**Table 6.** Predictive Test of Hedge Fund Activeness and Performance: Fama-MacBeth Regression

This table reports Fama-MacBeth regression results for hedge fund performance on hedge fund activeness and control variables. For each month we calculate four hedge fund performance measures—average raw return (RET$_{t+1,t+12}$), alpha, the Sharpe ratio (SR$_{t+1,t+12}$), and the manipulation-proof performance measure (MPPM3$_{t+1,t+12}$)—for the subsequent twelve months. ACT$_{t-12,t}$ is the measure of hedge fund activeness in the past twelve months. The four past performance measures are included. AGE is the fund age in years at month $t$. LOGSIZE is the natural logarithm of fund size at month $t$. NUMF is the number of systematic factors identified at month $t$. OFFSHORE is a dummy variable with 1 indicating an offshore vehicle. MFEE and PFEE are the management fee and performance fee in percentage, respectively. RESTRICTION is the restriction period defined as the sum of redemption notice period and lockup period in months stipulated by the fund. We also include dummy variables for hedge fund style which are suppressed for brevity. The left panel is for the full sample period 1995–2012, the middle panel is for the period 1995-2002, and the right panel is for the period post 2002. The numbers in the parentheses are $t$ statistics based on standard errors that are corrected for serial correlation using the Newey-West procedure. ***, ** and * denote significance at the level of 1%, 5%, and 10%, respectively.

| | *Dependent variable:* | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Full Sample | | | | Pre-2002 | | | | Post-2002 | | | |
| | $\alpha_{t+1:t+12}$ | AR$_{t+1:t+12}$ | SR$_{t+1:t+12}$ | MPPM3$_{t+1:t+12}$ | $\alpha_{t+1:t+12}$ | AR$_{t+1:t+12}$ | SR$_{t+1:t+12}$ | MPPM3$_{t+1:t+12}$ | $\alpha_{t+1:t+12}$ | AR$_{t+1:t+12}$ | SR$_{t+1:t+12}$ | MPPM3$_{t+1:t+12}$ |
| ACT$_{t-11:t}$ | 0.0019** | 0.0182 | -0.0215** | 0.0004 | 0.0049*** | 0.0765** | -0.0245 | 0.0068 | -0.0005 | -0.0284 | -0.0192 | -0.0047 |
| | (2.24) | (0.83) | (-2.02) | (0.05) | (4.07) | (2.27) | (-1.35) | (0.37) | (-1.04) | (-1.56) | (-1.52) | (-0.91) |
| $\alpha_{t+1:t+12}$ | 0.3602*** | | | | 0.3205*** | | | | 0.3920** | | | |
| | (14.38) | | | | (9.47) | | | | (12.41) | | | |
| AR$_{t-11:t}$ | | 0.4934*** | | | | 0.3936*** | | | | 0.5731*** | | |
| | | (8.21) | | | | (6.52) | | | | (6.67) | | |
| SR$_{t-11:t}$ | | | 0.3062*** | | | | 0.2954*** | | | | 0.2683*** | |
| | | | (10.60) | | | | (8.21) | | | | (6.73) | |
| MPPM3$_{t-11:t}$ | | | | 0.0946*** | | | | 0.0470 | | | | 0.1328*** |
| | | | | (2.80) | | | | (0.99) | | | | (3.11) |
| VOL$_{t-11:t}$ | -0.0354*** | -1.5838*** | -1.10*** | -1.1957*** | -0.0296* | -1.9893*** | -1.2080*** | -1.3959 | -0.0399*** | -1.2594*** | -1.0144*** | -1.0355 |
| | (-3.77) | (-7.07) | (-6.30) | (-2.83) | (-1.87) | (-5.83) | (-4.97) | (-2.37) | (-3.65) | (-4.94) | (-4.15) | (-1.77) |
| FLOW$_{t-11:t}$ | -0.0075*** | -0.2022*** | -0.1061*** | -0.0342* | -0.0118*** | -0.1662*** | -0.1591** | -0.0645* | -0.0041*** | -0.2309*** | -0.0637** | -0.0100 |
| | (-5.69) | (-6.20) | (-2.64) | (-1.78) | (-6.38) | (-4.27) | (-2.08) | (-1.91) | (-4.87) | (-4.86) | (-1.98) | (-0.57) |
| LOGSIZE | -0.0004*** | -0.0083*** | -0.0062*** | -0.0076*** | -0.0007*** | -0.0062 | -0.0109** | -0.0134*** | -0.0003*** | -0.0101*** | -0.0025 | -0.0031 |
| | (-4.78) | (-2.90) | (-2.20) | (-3.07) | (-4.26) | (-1.36) | (-2.23) | (-3.32) | (-3.78) | (-2.81) | (-0.93) | (-1.42) |
| AGE | -0.0002*** | -.0051*** | -0.0050*** | -0.0079 | -0.0012** | -0.0094*** | -0.0083*** | -0.0016 | -0.0000 | -0.0017 | -0.0024*** | -0.0008*** |
| | (-2.80) | (-3.38) | (-4.55) | (-2.00) | (-4.47) | (-4.29) | (-4.68) | (-1.32) | (-0.25) | (-1.53) | (-4.22) | (-2.66) |
| LOCKUP | 0.00004** | 0.0003 | -0.0001 | 0.0003 | 0.0001** | 0.0005 | -0.0002 | 0.0006 | 0.0000 | 0.0002 | -0.0001 | 0.0001 |
| | (2.36) | (0.66) | (-0.27) | (1.16) | (2.36) | (0.54) | (-0.25) | (1.26) | (1.56) | (0.37) | (-0.12) | (0.25) |
| NOTICE | 0.0003*** | 0.0212*** | 0.0174*** | 0.0027** | 0.0004** | 0.0365*** | 0.0232*** | 0.0043*** | 0.0002*** | 0.0090 | 0.0128*** | 0.0013 |
| | (3.35) | (3.44) | (5.08) | (2.00) | (2.21) | (4.14) | (4.67) | (2.75) | (2.98) | (1.55) | (3.50) | (0.80) |
| MFEE | -0.0022 | -2599 | -0.3035 | 0.1943 | -0.0266* | -0.4968 | 0.1173 | 0.4473 | 0.0174** | -0.0703 | -0.6402 | -0.0081 |
| | (-0.22) | (-0.53) | (-0.74) | (1.04) | (-1.77) | (-0.64) | (0.17) | (1.44) | (2.08) | (-0.12) | (-1.36) | (-0.04) |
| PFEE | 0.0011 | 0.0161 | -0.0232 | 0.0100 | 0.0008 | -0.0418 | -0.0597 | 0.0308* | 0.0013 | 0.0624 | 0.0059 | -0.0067 |
| | (1.06) | (0.36) | (-0.65) | (0.85) | (0.41) | (-0.52) | (-1.04) | (1.97) | (1.48) | (1.44) | (0.14) | (-0.45) |
| OFFSHORE | 0.0003** | 0.0090 | 0.0030 | 0.0034 | 0.0005 | 0.0189 | 0.0019 | 0.0048 | 0.0002** | 0.0011 | 0.0038 | 0.0022** |
| | (2.10) | (1.24) | (0.64) | (1.19) | (1.52) | (1.59) | (0.19) | (0.77) | (2.20) | (0.14) | (1.26) | (2.34) |
| $Adj.R^2(\%)$ | 18.63 | 16.86 | 25.45 | 17.73 | 18.59 | 18.81 | 31.10 | 19.36 | 18.66 | 31.79 | 20.01 | 16.43 |

## **Table 7.** Predictive Test of Hedge Fund Activeness and Performance: Panel Data Regression

This table presents results of the panel regression with time and style fixed effect. for hedge fund performance on hedge fund activeness and control variables. The variables are as described in Table 6. The numbers in the parentheses are $t$ statistics based on standard errors that are adjusted for fund clustering. ***, ** and * denote significance at the level of 1%, 5%, and 10%, respectively.

| | *Dependent variable:* | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Full Sample | | | | Pre-2002 | | | | Post-2002 | | | |
| | $\alpha_{t+1:t+12}$ | $AR_{t+1:t+12}$ | $SR_{t+1:t+12}$ | $MPPM3_{t+1:t+12}$ | $\alpha_{t+1:t+12}$ | $AR_{t+1:t+12}$ | $SR_{t+1:t+12}$ | $MPPM3_{t+1:t+12}$ | $\alpha_{t+1:t+12}$ | $AR_{t+1:t+12}$ | $SR_{t+1:t+12}$ | $MPPM3_{t+1:t+12}$ |
| $ACT_{t-11:t}$ | 0.0001 | −0.0289 | −0.0175** | −0.0016 | 0.0039*** | 0.0586* | −0.0056 | 0.0282 | −0.0006 | −0.0519*** | −0.0349*** | −0.0193*** |
| | (0.22) | (−1.58) | (−2.50) | (−0.24) | (3.54) | (1.66) | (−0.34) | (1.46) | (−1.21) | (−2.61) | (−5.25) | (−3.05) |
| $\alpha_{t+1:t+12}$ | 0.3404*** | | | | 0.2816*** | | | | 0.3729*** | | | |
| | (24.17) | | | | (12.11) | | | | (25.07) | | | |
| $AR_{t+1:t+12}$ | | 0.3261*** | | | | 0.1788* | | | | 0.3647*** | | |
| | | (4.73) | | | | (1.72) | | | | (7.83) | | |
| $SR_{t+1:t+12}$ | | | 0.2725*** | | | | 0.3205*** | | | | 0.2404*** | |
| | | | (26.57) | | | | (20.53) | | | | (23.24) | |
| $MPPM3_{t+1:t+12}$ | | | | 0.0045 | | | | 0.0169 | | | | −0.0063 |
| | | | | (0.56) | | | | (0.93) | | | | (−0.76) |
| $VOL_{t-11:t}$ | −0.0238*** | −1.6003*** | −0.9199*** | −0.9770*** | −0.0188*** | −2.0147*** | −1.1974*** | −1.4117*** | −0.0349*** | −1.5182*** | −0.5351*** | −0.6259*** |
| | (−6.06) | (−6.44) | (−10.92) | (−9.39) | (−2.87) | (−4.18) | (−5.53) | (−4.63) | (−8.01) | (−7.14) | (−8.09) | (−8.46) |
| $FLOW_{t-11:t}$ | −0.0064*** | −0.1533*** | −0.1284*** | −0.0134 | −0.0105*** | −0.0962 | −0.2019*** | −0.0373 | −0.0048*** | −0.1664*** | −0.1231*** | −0.0165 |
| | (−7.58) | (−2.98) | (−5.61) | (−1.07) | (−5.50) | (−1.02) | (−4.34) | (−1.34) | (−5.47) | (−3.27) | (−4.92) | (−1.30) |
| LOGSIZE | −0.0004*** | −0.0103** | −0.0066*** | −0.0077*** | −0.0007*** | −0.0043 | −0.0151*** | −0.0163*** | −0.0003*** | −0.0102** | −0.0026* | −0.0044*** |
| | (−7.40) | (−2.42) | (−4.72) | (−11.23) | (−5.67) | (−0.76) | (−5.36) | (−9.24) | (−4.78) | (−1.98) | (−1.88) | (−6.18) |
| AGE | −0.00004** | −0.0028*** | −0.0034*** | −0.0007*** | −0.0002*** | −0.0085*** | −0.0077*** | −0.0017** | −0.00001 | −0.0022** | −0.0030*** | −0.0007*** |
| | (−2.29) | (−2.75) | (−7.40) | (−2.68) | (−4.26) | (−3.64) | (−6.05) | (−2.18) | (−0.64) | (−2.06) | (−6.46) | (−2.77) |
| LOCKUP | 0.00002 | 0.0003 | −0.0003 | 0.0001 | 0.0001** | 0.0001 | −0.0010* | 0.0002 | 0.00001 | 0.0004 | −0.0001 | 0.0001 |
| | (1.57) | (0.34) | (−0.83) | (0.74) | (1.98) | (0.11) | (−1.65) | (0.67) | (1.01) | (0.34) | (−0.19) | (0.49) |
| NOTICE | 0.0003*** | 0.0209*** | 0.0173*** | 0.0027*** | 0.0005*** | 0.0490*** | 0.0292*** | 0.0054** | 0.0002** | 0.0139** | 0.0136*** | 0.0017 |
| | (3.15) | (3.30) | (6.37) | (2.65) | (2.71) | (4.54) | (5.78) | (2.42) | (2.29) | (2.17) | (4.98) | (1.51) |
| MFEE | −0.0016 | −0.0635 | −0.2232 | 0.1680 | −0.0254 | −0.1019 | 0.2935 | 0.4182 | 0.0141 | 0.2809 | −0.3194 | 0.1049 |
| | (−0.11) | (−0.09) | (−0.61) | (1.02) | (−0.82) | (−0.08) | (0.46) | (1.21) | (1.11) | (0.44) | (−0.87) | (0.62) |
| PFEE | 0.0015 | 0.0653 | −0.0208 | 0.0035 | 0.0022 | 0.0032 | −0.0289 | 0.0394 | 0.0013 | 0.0665 | −0.0225 | −0.0090 |
| | (1.23) | (0.97) | (−0.59) | (0.24) | (0.82) | (0.02) | (−0.44) | (1.31) | (1.01) | (0.94) | (−0.63) | (−0.57) |
| OFFSHORE | 0.0002 | 0.0077 | 0.0014 | 0.0010 | 0.0002 | 0.0120 | −0.0072 | −0.0010 | 0.0002 | 0.0066 | 0.0054 | 0.0019 |
| | (1.19) | (0.72) | (0.33) | (0.47) | (0.46) | (0.82) | (−0.91) | (−0.24) | (1.18) | (0.54) | (1.28) | (0.87) |
| Adj. $R^2$ (%) | 12.50 | 15.97 | 13.83 | 3.30 | 11.51 | 19.22 | 22.80 | 7.38 | 14.46 | 16.51 | 9.85 | 1.69 |

**Table 8.** Predictive Test of Hedge Fund Activeness and Performance: Robustness Check

This table reports the results of panel regression with time and style fixed effect for hedge fund performance on hedge fund activeness and control variables using different measures of activeness. Dependent variables and control variables are described as in Table 6. The results for control variables are suppressed for the sake of succinctness. In Panel A, the measure of activeness is computed based on risk exposures including the trend-following factors. In Panel B, the measure of activeness is defined as $\sum_{k=1}^{K} \sigma_{\beta_{k,t-11:t}}$ and denoted as $\text{ALTACT}_{t-11:t}$. In Panel C, we present results for the post-2002 period excluding years 2008 and 2009. The numbers in the parentheses are $t$ statistics based on standard errors that are adjusted for fund clustering. ***, ** and * denote significance at the level of 1%, 5%, and 10%, respectively.

Panel A: Including FH Trend-following Factors

| | Full Sample | | | | Pre-2002 | | | | Post-2002 | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $\alpha_{t+1:t+12}$ | $\text{AR}_{t+1:t+12}$ | $\text{SR}_{t+1:t+12}$ | $\text{MPPM3}_{t+1:t+12}$ | $\alpha_{t+1:t+12}$ | $\text{AR}_{t+1:t+12}$ | $\text{SR}_{t+1:t+12}$ | $\text{MPPM3}_{t+1:t+12}$ | $\alpha_{t+1:t+12}$ | $\text{AR}_{t+1:t+12}$ | $\text{SR}_{t+1:t+12}$ | $\text{MPPM3}_{t+1:t+12}$ |
| $\text{ACT}_{t-11:t}$ | 0.0029** | 0.0168 | 0.0031 | 0.0060 | 0.0098*** | 0.1190*** | 0.0072 | 0.0249 | 0.0009 | -0.0162 | −0.0109 | -0.0078 |
| | (2.47) | (0.98) | (0.42) | (0.82) | (4.17) | (3.99) | (0.43) | (1.31) | (1.00) | (-0.82) | (−1.48) | (-1.09) |
| $Adj.R^2(\%)$ | 19.66 | 26.49 | 13.81 | 3.30 | 8.18 | 29.03 | 22.79 | 3.98 | 9.68 | 26.19 | 9.79 | 2.37 |

*Panel B: Alternative Measure*

| | Full Sample | | | | Pre-2002 | | | | Post-2002 | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $\alpha_{t+1:t+12}$ | $\text{AR}_{t+1:t+12}$ | $\text{SR}_{t+1:t+12}$ | $\text{MPPM3}_{t+1:t+12}$ | $\alpha_{t+1:t+12}$ | $\text{AR}_{t+1:t+12}$ | $\text{SR}_{t+1:t+12}$ | $\text{MPPM3}_{t+1:t+12}$ | $\alpha_{t+1:t+12}$ | $\text{AR}_{t+1:t+12}$ | $\text{SR}_{t+1:t+12}$ | $\text{MPPM3}_{t+1:t+12}$ |
| $\text{ALTACT}_{t-11:t}$ | 0.0004 | -0.0198 | −0.0139** | 0.0027 | 0.0037*** | 0.0555* | 0.0018 | 0.0269 | −0.0004 | −0.0468** | −0.0308*** | −0.0130** |
| | (1.12) | (-1.21) | (−2.22) | (0.45) | (4.44) | (1.87) | (0.13) | (1.64) | (−1.05) | (−2.53) | (−5.02) | (−2.40) |
| $Adj.R^2(\%)$ | 12.51 | 15.97 | 13.82 | 3.29 | 11.68 | 19.24 | 22.80 | 7.41 | 14.46 | 16.51 | 9.85 | 1.67 |

Panel C: Post-2002 and Excluding 2008-2009

| | $\alpha_{t+1:t+12}$ | $\text{AR}_{t+1:t+12}$ | $\text{SR}_{t+1:t+12}$ | $\text{MPPM3}_{t+1:t+12}$ |
|---|---|---|---|---|
| $\text{ACT}_{t-11:t}$ | −0.0010** | −0.0714*** | −0.0336*** | −0.0119** |
| | (−2.11) | (−2.99) | (−4.42) | (−2.41) |
| $Adj.R^2(\%)$ | 17.68 | 16.58 | 12.38 | 1.94 |

**Table 9.** Impact of Activeness on Performance in Pre-2002 Period: Style Breakdown Analysis

This table presents the results of panel regression with time and style fixed effect for the style breakdown analysis of how hedge fund activeness affect fund performance in the pre-2002 period. Activeness is interacted with the six hedge fund styles. Variables are as described in Table 6. The numbers in the parentheses are $t$ statistics based on standard errors that are adjusted for fund clustering as well as time and style fixed effect. DT stands for directional traders, FOF for funds of hedge funds, MULT for multi-process, RELVAL for relative value, SS for security selection, and OTHER for other categories. ***, ** and * denote significance at the level of 1%, 5%, and 10%, respectively.

| | *Dependent variable:* | | | |
|---|---|---|---|---|
| | $\alpha_{t+1:t+12}$ | $AR_{t+1:t+12}$ | $SR_{t+1:t+12}$ | $MPPM3_{t+1:t+12}$ |
| ACT*DT | 0.0049*** | 0.1589*** | 0.0520** | 0.0140 |
| | (2.58) | (3.12) | (2.32) | (0.47) |
| ACT*FOF | 0.0020 | −0.0694 | −0.1062*** | 0.0788** |
| | (0.81) | (−0.73) | (−2.61) | (2.27) |
| ACT*MULT | 0.0035 | −0.1774** | −0.1315*** | 0.0821*** |
| | (1.55) | (−1.97) | (−2.61) | (2.75) |
| ACT*RELVAL | 0.0052* | −0.0772 | −0.0527 | 0.0338 |
| | (1.81) | (−0.60) | (−0.86) | (0.97) |
| ACT*SS | 0.0028** | 0.0689 | 0.0038 | 0.0225 |
| | (2.28) | (1.47) | (0.13) | (0.89) |
| ACT*OTHER | 0.0062 | −0.0076 | −0.1100 | −0.0556 |
| | (0.88) | (−0.06) | (−1.62) | (−0.87) |
| $\alpha_{t-11:t}$ | 0.2811*** | | | |
| | (12.13) | | | |
| $AR_{t-11:t}$ | | 0.1765* | | |
| | | (1.71) | | |
| $SR_{t-11:t}$ | | | 0.3148*** | |
| | | | (19.67) | |
| $MPPM3_{t-11:t}$ | | | | 0.0149 |
| | | | | (0.87) |
| $VOL_{t-11:t}$ | −0.0181*** | −1.9997*** | −1.1872*** | −1.4241*** |
| | (−2.74) | (−4.01) | (−4.96) | (−5.05) |
| $FLOW_{t-11:t}$ | −0.0105*** | −0.0933 | −0.1974*** | −0.0380 |
| | (−5.51) | (−1.00) | (−4.22) | (−1.37) |
| LOGSIZE | −0.0007*** | −0.0052 | −0.0156*** | −0.0162*** |
| | (−5.77) | (−0.94) | (−5.50) | (−9.23) |
| AGE | −0.0002*** | −0.0087*** | −0.0079*** | −0.0017** |
| | (−4.35) | (−3.75) | (−6.14) | (−2.17) |
| LOCKUP | 0.0001** | 0.0001 | −0.0011* | 0.0002 |
| | (2.03) | (0.07) | (−1.77) | (0.71) |
| NOTICE | 0.0005*** | 0.0488*** | 0.0293*** | 0.0055** |
| | (2.73) | (4.57) | (5.87) | (2.46) |
| MFEE | −0.0245 | 0.1161 | 0.4162 | 0.3872 |
| | (−0.80) | (0.09) | (0.65) | (1.11) |
| PFEE | 0.0023 | 0.0075 | −0.0246 | 0.0385 |
| | (0.86) | (0.06) | (−0.38) | (1.27) |
| OFFSHORE | 0.0002 | 0.0134 | −0.0064 | −0.0012 |
| | (0.45) | (0.92) | (−0.82) | (−0.30) |
| Adj. $R^2$ | 11.59 | 19.52 | 22.98 | 7.49 |

**Table 10.** Summary Statistics for Hedge Funds

This table presents descriptive statistics for hedge fund characteristics and monthly net-of-fee returns. Fund characteristics include number of observations, average asset under management in $M, a dummy variable with 1 denoting offshore vehicle, redemption notice period (days), lockup period (months), management fee, performance fee, and whether or not using high water mark. Average returns and skewness of returns are summarized.

| Variable | N | Mean | SD | 5th Pctl | 25th Pctl | Median | 75th Pctl | 95th Pctl |
|---|---|---|---|---|---|---|---|---|
| Return | 307,992 | 0.88 | 5.47 | -6.39 | -1.05 | 0.77 | 2.78 | 8.18 |
| Skew | 3024 | -0.02 | 1.32 | -1.65 | -0.58 | -0.06 | 0.48 | 1.77 |
| AvgAsset | 3024 | 108.63 | 227.39 | 7.05 | 18.44 | 42.37 | 109.79 | 398.75 |
| Obs | 3024 | 101.82 | 53.11 | 39.00 | 59.00 | 87.00 | 134.00 | 209.00 |
| MFee | 2959 | 1.37 | 0.60 | 0.90 | 1.00 | 1.50 | 1.50 | 2.00 |
| PFee | 2969 | 18.91 | 4.69 | 10.00 | 20.00 | 20.00 | 20.00 | 20.00 |
| HighWaterMark | 3020 | 0.76 | 0.43 | 0.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| LockupMonths | 2752 | 5.23 | 6.96 | 0.00 | 0.00 | 0.00 | 12.00 | 12.00 |
| NoticePeriod (in Days) | 2819 | 38.11 | 26.23 | 1.00 | 30.00 | 30.00 | 45.00 | 90.00 |
| Offshore | 3024 | 0.47 | 0.50 | 0.00 | 0.00 | 0.00 | 1.00 | 1.00 |

**Table 11.** Summary Statistics for Factors

This table presents descriptive statistics for Fama-French (1993) factors and the ten anomaly factors we chose. Panel A reports mean factor returns, Sharpe ratios, and Fama-French alphas for anomaly factors. Panel B presents correlations between these factors. The ten anomalies are: momentum (MOM), accruals (ACC), percent accruals (PACC), total asset growth (TAG), abnormal capital investment (CI), net operating assets (NOA), return on assets (ROA), gross profitability (GP), sales-price ratio (SP), and net stock issuance (ISS). COMB is an equal-weighted average of the ten anomalies.

*Panel A: Factor Returns*

| | Mkt.RF | SMB | HML | MOM | ACC | PACC | TAG | CI | NOA | ROA | GP | SP | ISS | COMB |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Mean (in %) | 0.64 | 0.19 | 0.21 | 0.45 | 0.30 | 0.31 | 0.27 | 0.26 | 0.37 | 0.11 | 0.30 | 0.51 | 0.37 | 0.32 |
| Sharpe Ratio | 0.14 | 0.06 | 0.07 | 0.09 | 0.17 | 0.18 | 0.11 | 0.10 | 0.18 | 0.04 | 0.13 | 0.15 | 0.10 | 0.33 |
| FF $\alpha$ | | | | 0.73 | 0.29 | 0.36 | 0.27 | 0.25 | 0.33 | 0.12 | 0.29 | 0.61 | 0.37 | 0.37 |
| $t_\alpha$ | | | | 2.41 | 2.57 | 3.43 | 1.76 | 1.64 | 2.58 | 0.80 | 1.94 | 2.87 | 1.57 | 6.11 |

*Panel B: Correlation Matrix*

| | Mkt.RF | SMB | HML | MOM | ACC | PACC | TAG | CI | NOA | ROA | GP | SP | ISS | COMB |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Mkt.RF | 1.00 | 0.25 | -0.23 | -0.27 | 0.06 | -0.06 | -0.03 | 0.01 | 0.03 | 0.00 | 0.03 | -0.14 | -0.03 | -0.19 |
| SMB | 0.25 | 1.00 | -0.35 | 0.09 | 0.04 | -0.03 | -0.03 | 0.05 | 0.04 | -0.00 | 0.02 | -0.10 | 0.02 | 0.04 |
| HML | -0.23 | -0.35 | 1.00 | -0.15 | -0.08 | -0.18 | 0.05 | -0.04 | 0.09 | -0.06 | -0.02 | -0.04 | 0.02 | -0.13 |
| MOM | -0.27 | 0.09 | -0.15 | 1.00 | 0.02 | 0.05 | -0.10 | 0.06 | -0.09 | 0.14 | -0.12 | -0.04 | -0.03 | 0.50 |
| ACC | 0.06 | 0.04 | -0.08 | 0.02 | 1.00 | 0.35 | -0.10 | 0.19 | 0.29 | 0.31 | -0.13 | -0.31 | -0.23 | 0.19 |
| PACC | -0.06 | -0.03 | -0.18 | 0.05 | 0.35 | 1.00 | 0.30 | -0.01 | -0.13 | 0.42 | -0.46 | 0.32 | 0.17 | 0.48 |
| TAG | -0.03 | -0.03 | 0.05 | -0.10 | -0.10 | 0.30 | 1.00 | -0.17 | 0.05 | 0.05 | -0.23 | 0.55 | 0.55 | 0.56 |
| CI | 0.01 | 0.05 | -0.04 | 0.06 | 0.19 | -0.01 | -0.17 | 1.00 | 0.22 | 0.17 | 0.02 | -0.23 | -0.15 | 0.23 |
| NOA | 0.03 | 0.04 | 0.09 | -0.09 | 0.29 | -0.13 | 0.05 | 0.22 | 1.00 | 0.13 | 0.20 | -0.45 | -0.19 | 0.12 |
| ROA | 0.00 | -0.00 | -0.06 | 0.14 | 0.31 | 0.42 | 0.05 | 0.17 | 0.13 | 1.00 | -0.66 | -0.20 | -0.42 | 0.15 |
| GP | 0.03 | 0.02 | -0.02 | -0.12 | -0.13 | -0.46 | -0.23 | 0.02 | 0.20 | -0.66 | 1.00 | 0.00 | 0.09 | -0.06 |
| SP | -0.14 | -0.10 | -0.04 | -0.04 | -0.31 | 0.32 | 0.55 | -0.23 | -0.45 | -0.20 | 0.00 | 1.00 | 0.59 | 0.50 |
| ISS | -0.03 | 0.02 | 0.02 | -0.03 | -0.23 | 0.17 | 0.55 | -0.15 | -0.19 | -0.42 | 0.09 | 0.59 | 1.00 | 0.54 |
| COMB | -0.19 | 0.04 | -0.13 | 0.50 | 0.19 | 0.48 | 0.56 | 0.23 | 0.12 | 0.15 | -0.06 | 0.50 | 0.54 | 1.00 |

**Table 12.** Hedge Fund Returns and Anomalies

This table reports pooled regression of hedge fund returns on the Fama-French (1993) factors and the ten anomaly factors. The ten anomalies are: momentum (MOM), accruals (ACC), percent accruals (PACC), total asset growth (TAG), abnormal capital investment (CI), net operating assets (NOA), return on assets (ROA), gross profitability (GP), sales-price ratio (SP), and net stock issuance (ISS). COMB is an equal-weighted average of the ten anomalies. $^{***}$, $^{**}$ and $^{*}$ denote significance at the level of 1%, 5%, and 10%, respectively.

| | *Dependent variable: RET* | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| Constant | 0.0033$^{***}$ | 0.0029$^{***}$ | 0.0027$^{***}$ |
| | (38.17) | (31.67) | (28.96) |
| Mkt.RF | 0.3296$^{***}$ | 0.3539$^{***}$ | 0.3404$^{***}$ |
| | (57.58) | (63.69) | (60.04) |
| SMB | 0.1461$^{***}$ | 0.1274$^{***}$ | 0.1451$^{***}$ |
| | (28.09) | (24.94) | (27.98) |
| HML | −0.0326$^{***}$ | −0.0336$^{***}$ | −0.0212$^{***}$ |
| | (−5.03) | (−5.32) | (−3.31) |
| COMB | | | 0.2037$^{***}$ |
| | | | (20.33) |
| MOM | | 0.0602$^{***}$ | |
| | | (21.41) | |
| ACC | | 0.0220$^{***}$ | |
| | | (4.47) | |
| PACC | | −0.1221$^{***}$ | |
| | | (−18.76) | |
| TAG | | 0.0125$^{**}$ | |
| | | (2.14) | |
| CI | | 0.0080$^{*}$ | |
| | | (1.95) | |
| GP | | −0.0282$^{***}$ | |
| | | (−6.30) | |
| NOA | | 0.0937$^{***}$ | |
| | | (17.96) | |
| ROA | | 0.0155$^{**}$ | |
| | | (2.33) | |
| ISS | | 0.0231$^{***}$ | |
| | | (4.01) | |
| SP | | 0.0164$^{***}$ | |
| | | (4.53) | |
| Adj. $R^2$ (%) | 13.34 | 14.07 | 13.52 |

**Table 13.** Properties of Hedge Fund Activities in Exploiting Stock Anomalies

This table reports shows properties of hedge fund activities in exploiting stock anomalies. Panel A presents the transition matrix for the measure of exploiting anomalies from the prior 12 months to the subsequent 12 months. Panel B presents Fama-MacBeth (1973) regression and panel regression results (with time fixed effect) for explaining hedge fund activities in exploiting stock anomalies. $T$-statistics in the Fama-MacBeth regression is based on Newey-West standard errors and $t$-statistics in the panel regression is clustered at the fund level. ***, ** and * denote significance at the level of 1%, 5%, and 10%, respectively.

Panel A: Transition Matrix

| | Q1 | 2 | 3 | Q4 |
|---|---|---|---|---|
| Q1 | 65.83 | 22.41 | 7.80 | 3.96 |
| 2 | 21.43 | 43.29 | 27.05 | 8.23 |
| 3 | 7.79 | 26.56 | 44.13 | 21.53 |
| Q4 | 4.90 | 7.81 | 20.96 | 66.34 |

Panel B: Determinants of Activities in Exploiting Anomalies

| | *Dependent variable:* $Exploit_{t+1:t+12}$ | |
|---|---|---|
| | FM | Panel |
| $\text{Exploit}_{t-11:t}$ | 0.7421*** | 0.7025*** |
| | (18.16) | (69.87) |
| alpha | -0.0015 | $-0.0022$ |
| | (-0.89) | $(-1.05)$ |
| LogAge | 0.0318** | 0.0173 |
| | (2.07) | (3.45) |
| LogAsset | 0.0009 | 0.0008 |
| | (0.28) | (0.46) |
| MFee | 0.0129 | 0.0260*** |
| | (1.32) | (3.84) |
| PFee | 0.0015** | 0.0017** |
| | (2.31) | (2.62) |
| HighWaterMark | -0.0146* | $-0.0080$ |
| | (-1.72) | $(-1.04)$ |
| LockupMonths | -0.0012 | $-0.0009$* |
| | (-1.36) | $(-1.86)$ |
| NoticePeriod | 0.0003** | 0.0003* |
| | (2.49) | (1.92) |
| Offshore | 0.0121 | 0.0097 |
| | (1.22) | (1.56) |
| Adj. $R^2$ (%) | 54.37 | 49.87 |

**Table 14.** Exploiting Anomalies and Hedge Fund Performance

This table reports portfolio sorting results of hedge fund performance on prior activities in exploiting stock anomalies. The first 4 columns are for Fama-French (1993) alphas in the subsequent 1, 3, 6, and 12 months. The last column is for the appraisal ratio in the subsequent 12 months, calculated as alpha divided by the standard deviation of monthly abnormal returns. The $t$-statistics in the parentheses are based on the Newey-West standard errors.

| Group | $\text{Alpha}_1$ | $\text{Alpha}_3$ | $\text{Alpha}_6$ | $\text{Alpha}_{12}$ | AR |
|---|---|---|---|---|---|
| 1 (Low) | 0.31 | 0.31 | 0.31 | 0.31 | 0.07 |
| 2 | 0.29 | 0.28 | 0.27 | 0.27 | 0.09 |
| 3 | 0.27 | 0.30 | 0.28 | 0.26 | 0.12 |
| 4 | 0.25 | 0.25 | 0.27 | 0.27 | 0.14 |
| 5 | 0.26 | 0.26 | 0.27 | 0.28 | 0.16 |
| 6 | 0.26 | 0.27 | 0.29 | 0.30 | 0.18 |
| 7 | 0.29 | 0.29 | 0.31 | 0.31 | 0.15 |
| 8 | 0.29 | 0.29 | 0.31 | 0.34 | 0.14 |
| 9 | 0.35 | 0.37 | 0.37 | 0.38 | 0.13 |
| 10 (High) | 0.46 | 0.49 | 0.50 | 0.50 | 0.12 |
| 10 - 1 | 0.16 | 0.17 | 0.19 | 0.18 | 0.05 |
| *t-stat* | (1.78) | (2.17) | (2.41) | (2.34) | (2.55) |

**Table 15.** Hedge Fund Exploiting Anomalies and Performance: Fama-MacBeth Regression

This table reports the Fama-MacBeth regression results of hedge fund performance on hedge fund activities in exploiting anomalies ($Exploit$). The control variables include distinctiveness ($Distinct$), R-squared from regressing hedge fund returns on Fama-French (1993) factors, past performance, natural logarithm of fund age and size ($LogAge$ and $LogAsset$), management fee ($MFee$), performance fee ($PFee$), dummy variable for high water mark ($HighWaterMark$), lockup months, notice period and a dummy variable for offshore vehicles. The $t$-statistics in the parentheses are based on the Newey-West standard errors. ***, ** and * denote significance at the level of 1%, 5%, and 10%, respectively.

| | *Dependent variable:* | |
|---|---|---|
| | (1) | (2) |
| | $Alpha_{t+1:t+12}$ | $AR_{t+1:t+12}$ |
| Exploit | 0.1244*** | 0.0176 |
| | (2.42) | (1.48) |
| Distinct | 0.0069 | 0.0013 |
| | (0.58) | (0.35) |
| RSquared | −0.2296*** | −0.1131*** |
| | (−5.30) | (−7.77) |
| $\text{Alpha}_{t-11:t}$ | -0.0046 | |
| | (-0.48) | |
| $\text{AR}_{t-11:t}$ | | −0.0029 |
| | | (−0.41) |
| LogAge | -0.1384*** | -0.0599*** |
| | (-5.83) | (-5.44) |
| LogAsset | -0.0667*** | 0.0014 |
| | (-3.97) | (0.42) |
| MFee | 0.1182*** | 0.0461*** |
| | (2.48) | (3.79) |
| PFee | 0.0092*** | 0.0030*** |
| | (3.76) | (3.03) |
| HighWaterMark | 0.1063*** | 0.0181** |
| | (2.91) | (2.12) |
| LockupMonths | 0.0032 | -0.0005 |
| | (1.25) | (-0.86) |
| NoticePeriod | 0.0018*** | 0.0011*** |
| | (3.43) | (5.35) |
| Offshore | -0.0509* | -0.0143 |
| | (-1.79) | (-1.62) |
| Adj. $R^2$ (%) | 6.11 | 6.22 |

**Table 16.** Hedge Fund Exploiting Anomalies and Performance: Panel Regression

This table reports the panel regression results of hedge fund performance on hedge fund activities in exploiting anomalies ($Exploit$). The control variables are the same as those described in Table 15. Time fixed effect is included and standard errors are clustered at the fund level. ***, ** and * denote significance at the level of 1%, 5%, and 10%, respectively.

| | *Dependent variable:* | |
|---|---|---|
| | (1) | (2) |
| | $Alpha_{t+1:t+12}$ | $AR_{t+1:t+12}$ |
| Exploit | 0.0929*** | 0.0067 |
| | (3.28) | (1.19) |
| Distinct | 0.0072 | 0.0007 |
| | (0.88) | (0.27) |
| RSquared | −0.2224*** | −0.1153*** |
| | (−8.12) | (−10.01) |
| $\text{Alpha}_{t-11:t}$ | −0.0022 | |
| | (−0.30) | |
| $\text{AR}_{t-11:t}$ | | 0.0014 |
| | | (0.22) |
| LogAge | −0.1127*** | −0.0419*** |
| | (−6.17) | (−5.48) |
| LogAsset | −0.0537*** | 0.0018 |
| | (−6.71) | (0.42) |
| MFee | 0.0667 | 0.0323** |
| | (1.39) | (2.00) |
| PFee | 0.0076*** | 0.0014 |
| | (3.57) | (0.65) |
| HighWaterMark | 0.1162*** | 0.0292 |
| | (4.14) | (2.68) |
| LockupMonths | 0.0023 | −0.0005 |
| | (1.39) | (−0.77) |
| NoticePeriod | 0.0014*** | 0.0011*** |
| | (3.06) | (2.98) |
| Offshore | −0.0225 | −0.0039 |
| | (−0.98) | (−0.39) |
| Adj. $R^2$ (%) | 1.93 | 2.68 |

**Table 17.** Hedge Fund Exploiting Anomalies and Performance: Crowdedness and Competition

This table reports the panel regression results of hedge fund performance on hedge fund activities in exploiting anomalies ($Exploit$). Crowdedness and number of new funds are interacted with $Exploit$. The control variables are the same as those described in Table 15. Time fixed effect is included and standard errors are clustered at the fund level. ***, ** and * denote significance at the level of 1%, 5%, and 10%, respectively.

| | *Dependent variable:* | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| | $Alpha_{t+1:t+12}$ | $Alpha_{t+1:t+12}$ | $AR_{t+1:t+12}$ | $AR_{t+1:t+12}$ |
| Exploit | 0.1039*** | 0.1004*** | 0.0143** | 0.0098* |
| | (3.39) | (3.37) | (2.34) | (1.69) |
| Exploit * Crowd | −0.2040 | | −0.1410*** | |
| | (−1.52) | | (−4.22) | |
| Exploit * Newfund | | −0.1008** | | −0.0406*** |
| | | (−2.07) | | (−3.48) |
| Distinct | 0.0071 | 0.0074 | 0.0007 | 0.0008 |
| | (0.87) | (0.90) | (0.25) | (0.30) |
| RSquared | −0.2161*** | −0.2170*** | −0.1109*** | −0.1131*** |
| | (−7.84) | (−7.91) | (−9.60) | (−9.84) |
| $\text{Alpha}_{t-11:t}$ | −0.0021 | −0.0020 | | |
| | (−0.30) | (−0.28) | | |
| $\text{AR}_{t-11:t}$ | | | 0.0013 | 0.0015 |
| | | | (0.20) | (0.22) |
| LogAge | −0.1129*** | −0.1144*** | −0.0420*** | −0.0426*** |
| | (−6.19) | (−6.26) | (−5.51) | (−5.58) |
| LogAsset | −0.0536*** | −0.0534*** | 0.0018 | 0.0019 |
| | (−6.70) | (−6.69) | (0.42) | (0.44) |
| MFee | 0.0682 | 0.0684 | 0.0329** | 0.0333** |
| | (1.43) | (1.43) | (2.08) | (2.05) |
| PFee | 0.0076*** | 0.0076*** | 0.0011 | 0.0011 |
| | (3.56) | (3.58) | (0.65) | (0.66) |
| HighWaterMark | 0.1167*** | 0.1167*** | 0.0295*** | 0.0295*** |
| | (4.17) | (4.17) | (2.70) | (2.70) |
| LockupMonths | 0.0023 | 0.0023 | −0.0004 | −0.0005 |
| | (1.42) | (1.38) | (−0.71) | (−0.78) |
| NoticePeriod | 0.0014*** | 0.0014*** | 0.0011*** | 0.0011*** |
| | (3.03) | (3.04) | (2.97) | (2.98) |
| Offshore | −0.0227 | −0.0233 | −0.0107 | −0.0108 |
| | (−1.00) | (−1.01) | (−1.15) | (−1.16) |
| Adj. $R^2$ (%) | 2.33 | 2.33 | 2.73 | 2.77 |

**Table 18.** Hedge Fund Exploiting Anomalies and Performance: Alternative Measure I

This table reports the panel regression results of hedge fund performance on an alternative measure of hedge fund activities in exploiting anomalies ($Involve$). Crowdedness and number of new funds are interacted with $Involve$. The control variables are the same as those described in Table 15. Time fixed effect is included and standard errors are clustered at the fund level. ***, ** and * denote significance at the level of 1%, 5%, and 10%, respectively.

| | *Dependent variable:* | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| | $Alpha_{t+1:t+12}$ | $Alpha_{t+1:t+12}$ | $AR_{t+1:t+12}$ | $AR_{t+1:t+12}$ |
| Involve | 1.0510*** | 0.9903*** | 0.1369* | 0.1213* |
| | (4.68) | (4.28) | (1.79) | (1.67) |
| Involve * Crowd | −4.7554*** | | −1.0854** | |
| | (−4.00) | | (−2.74) | |
| Involve * Newfund | | −1.3485*** | | −0.2952** |
| | | (−3.56) | | (−2.27) |
| Distinct | 0.0073 | 0.0071 | 0.0007 | 0.0007 |
| | (0.89) | (0.87) | (0.27) | (0.25) |
| RSquared | −0.2080*** | −0.2124*** | −0.1122*** | −0.1133*** |
| | (−7.60) | (−7.79) | (−9.52) | (−9.71) |
| $\text{Alpha}_{t-11:t}$ | −0.0022 | −0.0022 | | |
| | (−0.31) | (−0.31) | | |
| $\text{AR}_{t-11:t}$ | | | 0.0014 | 0.0014 |
| | | | (0.21) | (0.21) |
| LogAge | −0.1191*** | −0.1217*** | −0.0425*** | −0.0431*** |
| | (−6.48) | (−6.58) | (−5.52) | (−5.60) |
| LogAsset | −0.0540*** | −0.0538*** | 0.0017 | 0.0018 |
| | (−6.79) | (−6.75) | (0.42) | (0.42) |
| MFee | 0.0688 | 0.0689 | 0.0324** | 0.0325** |
| | (1.45) | (1.45) | (2.02) | (2.02) |
| PFee | 0.0074*** | 0.0075*** | 0.0011 | 0.0011 |
| | (3.52) | (3.52) | (0.64) | (0.63) |
| HighWaterMark | 0.1109*** | 0.1099*** | 0.0286*** | 0.0285*** |
| | (3.97) | (3.94) | (2.62) | (2.61) |
| LockupMonths | 0.0025 | 0.0024 | −0.0005 | −0.0005 |
| | (1.49) | (1.43) | (−0.72) | (−0.76) |
| NoticePeriod | 0.0014*** | 0.0014*** | 0.0011*** | 0.0011*** |
| | (3.09) | (3.09) | (2.96) | (2.97) |
| Offshore | −0.0189 | −0.0192 | −0.0101 | −0.0102 |
| | (−0.81) | (−0.83) | (−1.09) | (−1.10) |
| Adj. $R^2$ (%) | 2.36 | 2.30 | 2.72 | 2.73 |

**Table 19.** Hedge Fund Exploiting Anomalies and Performance: Alternative Measure II

This table reports the panel regression results of hedge fund performance on an alternative measure of hedge fund activities in exploiting anomalies ($BCOMB$). Crowdedness and number of new funds are interacted with $BCOMB$. The control variables are the same as those described in Table 15. Time fixed effect is included and standard errors are clustered at the fund level. ***, ** and * denote significance at the level of 1%, 5%, and 10%, respectively.

| | *Dependent variable:* | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| | $Alpha_{t+1:t+12}$ | $Alpha_{t+1:t+12}$ | $AR_{t+1:t+12}$ | $AR_{t+1:t+12}$ |
| BCOMB | 0.0475*** | 0.0379** | 0.0194*** | 0.0151*** |
| | (2.58) | (2.07) | (4.51) | (3.62) |
| BCOMB * Crowd | −0.4212*** | | −0.1501*** | |
| | (−4.77) | | (−6.10) | |
| BCOMB * Newfund | | −0.1017*** | | −0.0258*** |
| | | (−3.32) | | (−3.15) |
| Distinct | 0.0071 | 0.0075 | 0.0006 | 0.0007 |
| | (0.88) | (0.91) | (0.23) | (0.27) |
| RSquared | −0.1960*** | −0.2089*** | −0.1039*** | −0.1094*** |
| | (−6.85) | (−7.35) | (−8.94) | (−9.47) |
| $\text{Alpha}_{t-11:t}$ | −0.0022 | −0.0019 | | |
| | (−0.31) | (−0.30) | | |
| $\text{AR}_{t-11:t}$ | | | 0.0012 | 0.0014 |
| | | | (0.18) | (0.21) |
| LogAge | −0.1142*** | −0.1176*** | −0.0429*** | −0.0435*** |
| | (−6.26) | (−6.43) | (−5.62) | (−5.66) |
| LogAsset | −0.0544*** | −0.0539*** | 0.0015 | 0.0016 |
| | (−6.76) | (−6.76) | (0.36) | (0.38) |
| MFee | 0.0717 | 0.0708 | 0.0323** | 0.0317** |
| | (1.50) | (1.48) | (2.01) | (1.98) |
| PFee | 0.0075*** | 0.0075*** | 0.0011 | 0.0010 |
| | (3.56) | (3.57) | (0.59) | (0.60) |
| HighWaterMark | 0.1186*** | 0.1179*** | 0.0306*** | 0.0304*** |
| | (4.24) | (4.20) | (2.81) | (2.78) |
| LockupMonths | 0.0025 | 0.0023 | −0.0003 | −0.0004 |
| | (1.52) | (1.41) | (−0.53) | (−0.63) |
| NoticePeriod | 0.0014*** | 0.0014*** | 0.0011*** | 0.0011*** |
| | (3.03) | (3.07) | (2.92) | (2.94) |
| Offshore | −0.0207 | −0.0209 | −0.0113 | −0.0113 |
| | (−0.89) | (−0.90) | (−1.22) | (−1.22) |
| Adj. $R^2$ (%) | 2.27 | 2.26 | 2.86 | 2.83 |

**Table 20.** Skewness of Hedge Fund Returns and Activities in Exploiting Anomalies

This table reports the panel regression results of hedge fund return skewness on an measures of hedge fund activities in exploiting anomalies and interactions with crowdedness. The control variables are the same as those described in Table 15. Time fixed effect is included and standard errors are clustered at the fund level. ***, ** and * denote significance at the level of 1%, 5%, and 10%, respectively.

| | *Dependent variable: Skew* | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| Exploit | 0.0435*** | | |
| | (2.59) | | |
| Involve | | 0.6314*** | |
| | | (3.75) | |
| BCOMB | | | 0.0101 |
| | | | (0.82) |
| Exploit * Crowd | −0.2259** | | |
| | (−2.29) | | |
| Involve * Crowd | | −4.4313*** | |
| | | (−4.56) | |
| BCOMB * Crowd | | | −0.2545*** |
| | | | (−3.84) |
| Distinct | −0.0075 | −0.0073 | −0.0074 |
| | (−1.41) | (−1.37) | (−1.39) |
| RSquared | −0.2873*** | −0.2824*** | −0.2841*** |
| | (−13.18) | (−12.98) | (−12.97) |
| $\text{Alpha}_{t-11:t}$ | 0.0118** | 0.0118** | 0.0119** |
| | (2.31) | (2.30) | (2.31) |
| LogAge | 0.0098 | 0.0070 | 0.0093 |
| | (0.62) | (0.44) | (0.59) |
| LogAsset | −0.0182*** | −0.0183*** | −0.0181*** |
| | (−2.81) | (−2.84) | (−2.78) |
| MFee | 0.0153 | 0.0142 | 0.0172 |
| | (0.80) | (0.74) | (0.90) |
| PFee | −0.0002 | −0.0003 | −0.0001 |
| | (−0.06) | (−0.13) | (−0.04) |
| HighWaterMark | 0.0106 | 0.0079 | 0.0100 |
| | (0.43) | (0.32) | (0.41) |
| LockupMonths | 0.0013 | 0.0014 | 0.0013 |
| | (0.95) | (1.02) | (0.90) |
| NoticePeriod | 0.0005 | 0.0005 | 0.0005 |
| | (1.25) | (1.21) | (1.26) |
| Offshore | −0.0039 | −0.0021 | −0.0021 |
| | (−0.19) | (−0.10) | (−0.10) |
| Adj. $R^2$ (%) | 1.84 | 1.98 | 1.89 |

**Table 21.** Hedge Fund Flows and Activities in Exploiting Anomalies

This table reports the panel regression results of hedge fund flows on an measures of hedge fund activities in exploiting anomalies and interactions with crowdedness. Dependent variables are fund flows in subsequent 3 months and subsequent 12 months. The control variables are the same as those described in Table 15. In addition, the cumulative past returns is included as another control variable. Time fixed effect is included and standard errors are clustered at the fund level. ***, ** and * denote significance at the level of 1%, 5%, and 10%, respectively.

| | *Dependent variable: Fund Flows* | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | $Flow_{t:t+3}$ | $Flow_{t:t+3}$ | $Flow_{t:t+3}$ | $Flow_{t:t+12}$ | $Flow_{t:t+12}$ | $Flow_{t:t+12}$ |
| Exploit | −0.0002 | | | −0.0008 | | |
| | (−0.20) | | | (−0.99) | | |
| Involve | | 0.0060 | | | 0.0037 | |
| | | (0.68) | | | (0.41) | |
| BCOMB | | | 0.0002 | | | −0.0003 |
| | | | (0.42) | | | (−0.44) |
| Exploit * Crowd | 0.0003 | | | −0.0012 | | |
| | (0.06) | | | (−0.29) | | |
| Involve * Crowd | | −0.0320 | | | −0.0553 | |
| | | (−0.66) | | | (−1.16) | |
| BCOMB * Crowd | | | −0.0089*** | | | −0.0061** |
| | | | (−3.01) | | | (−2.24) |
| Distinct | −0.0008 | −0.0008 | −0.0008 | −0.0002 | −0.0002 | −0.0002 |
| | (−1.49) | (−1.49) | (−1.49) | (−0.59) | (−0.59) | (−0.59) |
| RSquared | −0.0063*** | −0.0062*** | −0.0060*** | −0.0058*** | −0.0057*** | −0.0057*** |
| | (−5.10) | (−5.00) | (−4.74) | (−5.07) | (−4.97) | (−4.95) |
| $\text{CumRet}_{t-11:t}$ | 0.0533*** | 0.0533*** | 0.0535*** | 0.0345*** | 0.0345*** | 0.0346*** |
| | (17.13) | (17.13) | (17.09) | (15.50) | (15.48) | (15.54) |
| $\text{Alpha}_{t-11:t}$ | −0.0006* | −0.0006* | −0.0006* | −0.0005 | −0.0005 | −0.0005 |
| | (−1.77) | (−1.77) | (−1.77) | (−1.54) | (−1.53) | (−1.53) |
| LogAge | −0.0169*** | −0.0170*** | −0.0170*** | −0.0112*** | −0.0112*** | −0.0113*** |
| | (−18.69) | (−18.70) | (−18.80) | (−12.92) | (−12.86) | (−13.04) |
| LogAsset | −0.0044*** | −0.0044*** | −0.0044*** | −0.0064*** | −0.0064*** | −0.0064*** |
| | (−13.14) | (−13.13) | (−13.11) | (−17.40) | (−17.39) | (−17.35) |
| MFee | −0.0008 | −0.0008 | −0.0006 | 0.0006 | 0.0006 | 0.0008 |
| | (−0.62) | (−0.63) | (−0.47) | (0.45) | (0.42) | (0.55) |
| PFee | −0.0001 | −0.0001 | −0.0001 | −0.0001 | −0.0001 | −0.0001 |
| | (−1.22) | (−1.25) | (−1.27) | (−0.86) | (−0.90) | (−0.87) |
| HighWaterMark | 0.0035** | 0.0035** | 0.0035** | 0.0038*** | 0.0038*** | 0.0037*** |
| | (2.53) | (2.51) | (2.53) | (2.61) | (2.60) | (2.58) |
| LockupMonths | −0.0001* | −0.0001 | −0.0001 | −0.0001* | −0.0001* | −0.0001** |
| | (−1.65) | (−1.62) | (−1.61) | (−1.95) | (−1.93) | (−1.98) |
| NoticePeriod | 0.00002 | 0.00002 | 0.00002 | 0.00004* | 0.00004* | 0.00004* |
| | (1.24) | (1.20) | (1.18) | (1.72) | (1.66) | (1.67) |
| Offshore | −0.0011 | −0.0011 | −0.0011 | 0.0002 | 0.0001 | 0.0002 |
| | (−1.11) | (−1.13) | (−1.11) | (0.16) | (0.12) | (0.15) |
| Adj. $R^2$ | 6.84 | 6.84 | 6.88 | 13.05 | 13.04 | 13.09 |

**Table 22.** Sorting Uniqueness in Stock Holdings on Distinctiveness

This table reports the portfolio sorting results of hedge fund uniqueness in stock holdings on the Sun et al. (2012) distinctiveness. PI is the portfolio independence, JD is the Jaccard distance, CDS is the cosine distance, and IPI is the industry-level portfolio independence. Panel A uses the full sample, and Panel B uses a subsample, for which the correlation of reported hedge fund returns and holdings-based returns is at least 0.5. Portfolio 1 includes hedge funds with low distinctiveness, while portfolio 3 includes hedge funds with high distinctiveness. The fourth row is the difference between portfolio 3 and portfolio 1. The last row presents $t$-statistics based on Newey and West (1987) standard errors.

Panel A. All Sample

| | PI | JD | CDS | IPI |
|---|---|---|---|---|
| Portfolio 1 | 0.9713 | 0.9811 | 0.9839 | 0.6049 |
| Portfolio 2 | 0.9733 | 0.9823 | 0.9845 | 0.6119 |
| Portfolio 3 | 0.9711 | 0.9806 | 0.9833 | 0.6120 |
| Diff. | -0.0002 | -0.0005 | -0.0006 | 0.0071 |
| $t$-stat | (-0.15) | (-0.70) | (-1.01) | (2.39) |

Panle B. Subsample

| | PI | JD | CDS | IPI |
|---|---|---|---|---|
| Portfolio 1 | 0.9708 | 0.9806 | 0.9832 | 0.5953 |
| Portfolio 2 | 0.9739 | 0.9824 | 0.9849 | 0.6089 |
| Portfolio 3 | 0.9747 | 0.9833 | 0.9853 | 0.6088 |
| Diff. | 0.0039 | 0.0026 | 0.0021 | 0.0135 |
| $t$-stat | (2.28) | (3.75) | (3.02) | (3.52) |

**Table 23.** Sorting Hedge Fund Alpha on Uniqueness Measures

This table presents the portfolio sorting results of hedge fund alpha on uniqueness measures. DISTINCT is the Sun et al. (2012) distinctiveness, PI is the portfolio independence, JD is the Jaccard distance, CDS is the cosine distance, and IPI is the industry-level portfolio independence. Panel A uses the full sample, and Panel B uses a subsample, for which the correlation of reported hedge fund returns and holdings-based returns is at least 0.5. Portfolio 1 includes hedge funds with low uniqueness, while portfolio 3 includes hedge funds with high uniqueness. The fourth row is the difference between portfolio 3 and portfolio 1. The last row shows *t*-statistics based on Newey and West (1987) standard errors.

Panel A. All Sample

| | DISTINCT | PI | JD | CDS | IPI |
|---|---|---|---|---|---|
| Portfolio 1 | 0.2164 | 0.3580 | 0.3098 | 0.2914 | 0.3320 |
| Portfolio 2 | 0.3437 | 0.3247 | 0.2906 | 0.3016 | 0.3013 |
| Portfolio 3 | 0.4868 | 0.2465 | 0.3079 | 0.3126 | 0.2737 |
| Diff. | 0.2704 | -0.1115 | -0.0018 | 0.0212 | -0.0847 |
| *t*-stat | (4.13) | (-2.81) | (-0.04) | (0.38) | (-1.13) |

Panle B. Subsample

| | DISTINCT | PI | JD | CDS | IPI |
|---|---|---|---|---|---|
| Portfolio 1 | 0.1763 | 0.3057 | 0.3281 | 0.2580 | 0.3003 |
| Portfolio 2 | 0.2956 | 0.2933 | 0.1623 | 0.2553 | 0.2824 |
| Portfolio 3 | 0.5163 | 0.2049 | 0.2918 | 0.2703 | 0.2238 |
| Diff. | 0.3399 | -0.1008 | -0.0363 | 0.0123 | -0.1153 |
| *t*-stat | (4.31) | (-1.37) | (-0.68) | (0.16) | (-1.21) |

**Table 24.** Distinctiveness Based on Holdings

This table presents the portfolio sorting results for distinctiveness based on stock holdings. DISTINCT is the Sun et al. (2012) distinctiveness using reported hedge fund returns, and HDISTINCT is the distinctiveness based on hedge fund stock holdings. Panel A sorts HDISTINCT on DISTINCT. Panel B sorts hedge fund alpha on HDISTINCT. Portfolio 1 includes hedge funds with low distinctiveness, while portfolio 3 includes hedge funds with high distinctiveness. The fourth column is the difference between portfolio 3 and portfolio 1. The last column shows $t$-statistics based on Newey and West (1987) standard errors.

| Panel A: HDIST | | | | | |
|---|---|---|---|---|---|
| | Portfolio 1 | Portfolio 2 | Portfolio 3 | Diff. | $t$-stat |
| DISTINCT | 0.1281 | 0.1758 | 0.2144 | 0.0863 | (4.32) |

| Panel B: Alpha | | | | | |
|---|---|---|---|---|---|
| | Portfolio 1 | Portfolio 2 | Portfolio 3 | Diff. | $t$-stat |
| HDIST | 0.3658 | 0.2399 | 0.3331 | -0.0327 | (-0.49) |

**Table 25.** Hedge Fund Characteristics Sorted on UDR

This table presents the portfolio sorting results for hedge fund characteristics on UDR which measures the role of unreported actions. SIZE is the natural logarithm of average hedge fund AUM, AGE is the natural logarithm of hedge fund age, MFEE is the management fee (%), PFEE is the performance fee (%), LOCKUP is the lockup period (months), NOTICE is the redemption notice period (days). Portfolio 1 includes hedge funds with low UDR, while portfolio 3 includes hedge funds with high UDR. The fourth row is the difference between portfolio 3 and portfolio 1. The last row shows *t*-statistics based on Newey and West (1987) standard errors.

| | SIZE | AGE | MFEE | PFEE | LOCKUP | NOTICE |
|---|---|---|---|---|---|---|
| Portfolio 1 | 18.4160 | 2.2786 | 1.2689 | 18.1595 | 6.7916 | 42.2126 |
| Portfolio 2 | 18.8352 | 2.1708 | 1.3660 | 18.2224 | 6.5085 | 46.0781 |
| Portfolio 3 | 18.8301 | 2.0317 | 1.3915 | 17.5033 | 6.0059 | 41.4468 |
| Diff. | 0.4141 | 0.2469 | 0.1225 | -0.6562 | -0.7857 | -0.7658 |
| *t*-stat | (3.33) | (-13.01) | (3.80) | (-3.01) | (-2.09) | (-0.46) |

**Table 26.** Correlation Matrix

This table presents the correlation matrix for hedge fund performance measures and potential measures for fund manager skills. Alpha is the Fung and Hsieh (2004) seven-factor alpha, AR is the appraisal ratio, UDR is the measure for unobserved hedge fund actions, DISTINCT is the Sun et al. (2012) distinctiveness, TTR2 is the Titman and Tiu (2011) R-squared, ReGap is the return gap proposed by [57]. All variables are at the firm level. Numbers in bold indicate that they are significant at the 5% level.

| | Alpha | AR | UDR | DISTINCT | TTR2 | RetGap |
|---|---|---|---|---|---|---|
| Alpha | | **0.6882** | **0.0929** | **0.0717** | **-0.0723** | **0.0252** |
| AR | **0.8845** | | **0.1982** | **0.0589** | **-0.1319** | **0.0134** |
| UDR | **0.1246** | **0.1878** | | **0.5216** | **-0.6986** | 0.0077 |
| DISTINCT | **0.0901** | **0.0878** | **0.5969** | | **-0.5159** | -0.0039 |
| TTR2 | **-0.0941** | **-0.1238** | **-0.7052** | **-0.6619** | | -0.0252 |
| RetGap | **0.0151** | **0.0189** | **-0.0366** | -0.0104 | -0.0001 | |

**Table 27.** Hedge Fund Performance Sorted on UDR

This table presents the portfolio sorting results for hedge fund performance on UDR which measures the role of unreported actions. Alpha is the Fung and Hsieh (2004) seven-factor alpha, and AR is the appraisal ratio. Portfolio 1 includes hedge funds with low UDR, while portfolio 3 includes hedge funds with high UDR. The fourth row is the difference between portfolio 3 and portfolio 1. The last row shows *t*-statistics based on Newey and West (1987) standard errors.

| | Alpha | AR |
|---|---|---|
| Portfolio 1 | 0.2093 | 0.0459 |
| Portfolio 2 | 0.3298 | 0.1897 |
| Portfolio 3 | 0.4475 | 0.2460 |
| Diff. | 0.2382 | 0.2000 |
| *t*-stat | (2.14) | (6.84) |

**Table 28.** Hedge Fund Performance and Unobserved Actions: Fama-MacBeth Regression

This table presents the Fama-MacBeth (1973) regression results for hedge fund performance. In Panel A, alpha is the dependent variable, while the appraisal ratio is the dependent variable in Panel B. UDR which measures the role of unreported actions. DISTINCT is the Sun et al. (2012) distinctiveness. TTR2 is the Titman and Tiu (2011) R-squared. MFEE is the management fee (%). PFEE is the performance fee (%), LOCKUP is the lockup period (months). NOTICE is the redemption notice period (days). All variables are at the firm level. We suppress the intercepts. The numbers in parentheses are *t*-statistics based on Newey and West (1987) standard errors.

| | Panel A: Alpha | | | | | Panel B: AR | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| UDR | 0.0034 | | | 0.0016 | 0.0015 | 0.2689 | | | 0.2681 | 0.2863 |
| | (2.26) | | | (0.89) | (0.73) | (6.47) | | | (5.07) | (5.53) |
| DISTINCT | | 0.0035 | | 0.0020 | 0.0024 | | 0.1297 | | -0.0769 | -0.0238 |
| | | (2.38) | | (1.38) | (1.76) | | (2.33) | | (-1.32) | (-0.37) |
| TTR2 | | | -0.0037 | -0.0017 | -0.0018 | | | -0.2339 | -0.0776 | -0.0402 |
| | | | (-3.06) | (-1.32) | (-1.30) | | | (-6.38) | (-1.09) | (-0.55) |
| MFEE | | | | | 0.0018 | | | | | -0.0402 |
| | | | | | (1.66) | | | | | (-2.04) |
| PFEE | | | | | -0.0020 | | | | | 0.0037 |
| | | | | | (-0.31) | | | | | (1.51) |
| LOCKUP | | | | | 0.0001 | | | | | -0.0018 |
| | | | | | (0.95) | | | | | (-1.14) |
| NOTICE | | | | | -0.0016 | | | | | 0.0019 |
| | | | | | (-1.06) | | | | | (2.85) |
| Adj. $R^2$ (%) | 3.32 | 2.46 | 1.29 | 4.42 | 5.45 | 4.86 | 2.29 | 2.94 | 8.00 | 10.00 |

**Table 29.** Hedge Fund Performance and Unobserved Actions: Quantile Regression

This table presents the quantile regression results for hedge fund performance. We select the 5th, 25th, 50th, 75th, and the 95th percentiles. In Panel A, alpha is the dependent variable, while the appraisal ratio is the dependent variable in Panel B. UDR which measures the role of unreported actions. DISTINCT is the Sun et al. (2012) distinctiveness. TTR2 is the Titman and Tiu (2011) R-squared. MFEE is the management fee (%). PFEE is the performance fee (%), LOCKUP is the lockup period (months). NOTICE is the redemption notice period (days). All variables are at the firm level. We suppress the intercepts. The numbers in parentheses are *t*-statistics based on Bootstrap standard errors with 200 repetitions.

| | Panel A: Alpha | | | | | Panel B: AR | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | p5 | p25 | p50 | p75 | p95 | p5 | p25 | p50 | p75 | p95 |
| UDR | 0.0128 | 0.0071 | 0.0031 | 0.0010 | -0.0061 | 0.3211 | 0.2726 | 0.2380 | 0.2256 | 0.3725 |
| | (8.69) | (16.54) | (9.04) | (2.22) | (-5.15) | (9.25) | (15.17) | (14.18) | (13.67) | (11.85) |
| DISTINCT | -0.0020 | -0.0012 | 0.0008 | 0.0032 | 0.0101 | -0.1085 | -0.0582 | -0.0056 | -0.0301 | -0.1496 |
| | (-2.14) | (-2.61) | (2.12) | (7.56) | (7.49) | (-2.93) | (-2.73) | (-0.38) | (-2.13) | (-4.98) |
| TTR2 | 0.0076 | 0.0012 | 0.0006 | 0.0010 | -0.0020 | -0.0051 | 0.0466 | 0.0392 | -0.0629 | -0.0970 |
| | (4.99) | (2.19) | (1.71) | (2.04) | (-1.48) | (-0.13) | (2.09) | (2.28) | (-3.39) | (-2.55) |
| MFEE | -0.0002 | 0.0003 | 0.0007 | 0.0009 | 0.0035 | -0.0187 | 0.0059 | 0.0068 | -0.0012 | -0.0205 |
| | (-0.28) | (0.91) | (3.06) | (2.86) | (3.68) | (-0.84) | (0.49) | (0.74) | (-0.10) | (-1.02) |
| PFEE | 0.0001 | 0.0001 | 0.0000 | -0.00002 | -0.0002 | -0.0004 | 0.0016 | 0.0011 | -0.0001 | 0.0018 |
| | (1.13) | (2.21) | (1.24) | (-0.70) | (-2.33) | (-0.27) | (1.87) | (1.24) | (-0.06) | (1.23) |
| LOCKUP | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | -0.0022 | -0.0015 | -0.0020 | -0.0022 | -0.0019 |
| | (-0.64) | (-2.94) | (-2.49) | (0.28) | (0.73) | (-2.00) | (-2.60) | (-3.72) | (-3.13) | (-1.79) |
| NOTICE | 0.0001 | 0.0001 | 0.0000 | 0.0000 | -0.0001 | 0.0004 | 0.0007 | 0.0012 | 0.0016 | 0.0022 |
| | (4.58) | (4.72) | (2.06) | (-2.21) | (-8.52) | (1.33) | (3.83) | (6.89) | (8.09) | (6.24) |

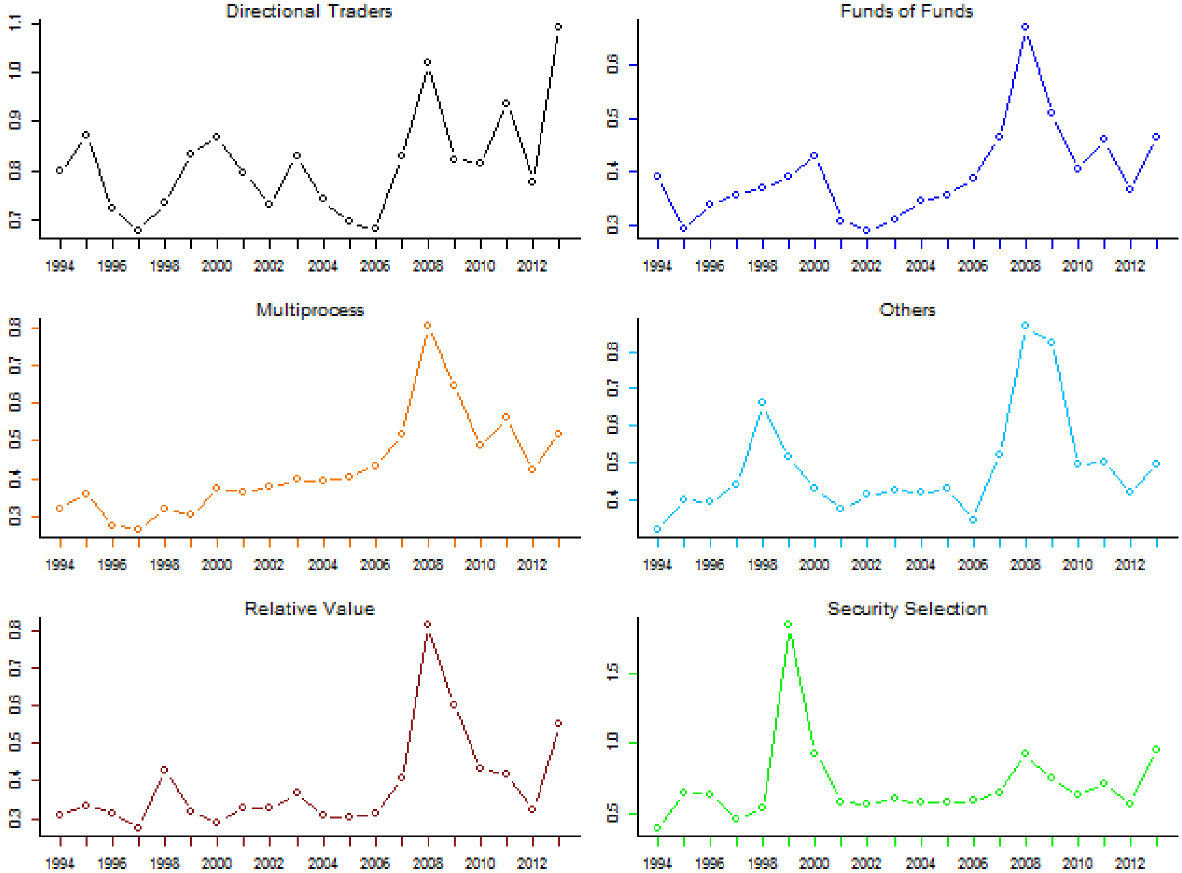
**Table 30.** Risk, Liquidity, Return Gap and Unobserved Actions

This table presents the Fama-MacBeth (1973) regression results for hedge fund total risk, liquidity, and return gap. In column (1), TotRisk – total risk – is the dependent variable. It is calculated as the standard deviation of future 12-month hedge fund returns. In column (2), Rho is the dependent variable. It is calculated as the first-order serial correlation of future 12-month hedge fund returns. In column (3), RetGap is the return gap between hedge fund reported returns and holdings-based returns. UDR measures the role of unreported actions. DISTINCT is the Sun et al. (2012) distinctiveness. TTR2 is the Titman and Tiu (2011) R-squared. MFEE is the management fee (%). PFEE is the performance fee (%), LOCKUP is the lockup period (months). NOTICE is the redemption notice period (days). All variables are at the firm level. We suppress the intercepts. The numbers in parentheses are *t*-statistics based on Newey and West (1987) standard errors.

| | TotRisk | Rho | RetGap |
|---|---|---|---|
| UDR | -0.0297 | 0.0449 | 0.0035 |
| | (-9.80) | (1.50) | (3.28) |
| DISTINCT | -0.0022 | -0.0653 | -0.0040 |
| | (-0.70) | (-4.02) | (-1.99) |
| TTR2 | 0.0040 | 0.0131 | 0.0015 |
| | (0.92) | (0.35) | (1.12) |
| PastRetGap | | | 0.1511 |
| | | | (3.78) |
| MFEE | 0.0039 | 0.0040 | 0.0007 |
| | (1.94) | (0.27) | (0.83) |
| PFEE | -0.0005 | 0.0007 | 0.0000 |
| | (-2.20) | (0.93) | (0.28) |
| LOCKUP | 0.0003 | 0.0000 | 0.0000 |
| | (2.39) | (0.05) | (0.63) |
| NOTICE | -0.0002 | 0.0011 | -0.0001 |
| | (-2.86) | (4.63) | (-4.08) |
| Adj. $R^2$ (%) | 18.03 | 6.41 | 13.64 |

**Figure 1.** Annual Hedge Fund Activeness

This figure presents yearly hedge fund activeness by hedge fund styles between 1995 and 2013. Hedge funds are grouped into six investment styles according to the method of MorningStar and Agarwal et al. (2009).



# APPENDIX
# SIMULATION OF ACTIVENESS

This section shows simulation results regarding two concerns. First, we make sure that the more "active" funds are detected as being indeed more "active". This is the building block of the subsequent analysis. Second, one would concern that as hedge funds become more active, a higher alpha is going to be more likely to be detected because the estimators of risk exposures become more inaccurate.

We use real factor data to conduct the simulation. The simulation is repeated 1000 times. For each of the simulation, we construct 3 types of funds in terms of how the risk exposures are managed. Five factors are randomly selected for the 3 funds. The first fund actively changes the risk exposures and its time-varying risk exposures follow a random walk. Specifically, the innovation in each risk exposure follows a Normal distribution with the standard deviation being 0.1. The rationale for the design that risk exposures follow random walks is that hedge funds are active yet their risk exposures, most of the time, should be still gradually changing rather than erratically changing such that they are independent through time. The second fund also change its risk exposures over time. The time series of the 5 risk exposures are assumed to follow random walks as well but the standard deviation of the innovation in each risk exposure is half of that of the first fund, i.e., 0.05. Thus the second fund is constructed to be less active than the first fund. The third fund has constant risk exposures over time. All variation in detected risk exposures should stem from estimation errors. Though for a hedge fund a decision to keep risk exposure unchanged is an active decision, our measure of activeness should categorize such a fund as being not active.

In the investment industry, people are very interested in the alpha, i.e., the risk-adjusted return of an investment (manager). For active fund managers, non-zero alphas justify the fees, often very high especially among hedge funds, that managers charge investors for active management. Thus it is imperative to estimate alpha correctly and accurately. A growing body of literature has noticed the implications of dynamic risk exposures to hedge fund performance evaluation. For example, Patton and Radamorai (2013) show that accounting for time-varying risk exposures enhances the appraisal of hedge fund performance. Here we address the concern that estimates of alpha tend to be high for active funds because of the accuracy of estimates for changing risk exposures.

For each simulation, we add a series of GARCH(1,1) errors. By construction, the returns of all the pseudo funds result from taking on factor risks and therefore there is no alpha on top of risk premiums for these funds. We run the simulation 1000 times, and calculate the activeness as well as the alpha for each simulation.

Table A1 shows the results of the simulation. Panel A provides the averages and standard deviations of the activeness measure, the alpha, and the individual $t$-statistics. On average, type 1 funds are the most active ones and type 3 funds are the least active. Not surprisingly, the standard deviations for the more active funds are higher. The means of alpha for the three types of funds are slightly less than 0 and are almost the same, -0.0025. The average of individual $t$-statistics for the most active funds is 0.0046, higher than that of least active funds, 0.0007. It appears that the estimation is able to generate higher measure of activeness for the more active funds. Moreover, the estimates of alpha are not systematically higher for the more active funds. This is confirmed by the $p$ values of statistical tests contained in Panel B. For each interested measure, between any two groups of funds, we perform $t$ test to test the null hypothesis that the means of these measures are equal, and we also perform the rank sum test to test the null hypothesis that the values are drawn from the same distribution. The $p$ values in Panel B show that, both the $t$ test and the rank sum test reject the null hypotheses for the measure of activeness, while the null hypotheses for the alpha and the $t$ statistics cannot be rejected at the 5% significance level, indicating that the alpha for all three types of pseudo funds are not significantly different from 0.

One of our approach to investigating the relationship between hedge fund activeness and performance is sorting funds into quintiles based on the estimated activeness and testing the difference of alpha between the top quintile and the bottom quintile. It is possible that the estimates of the alpha is related to estimation errors, leading to substantial differences between sorted groups. Our simulation enables us to "observe" the "true" factor loadings and activeness, thus we can study whether the results are driven by estimation errors. We utilize two measures of estimation errors, namely, the difference between the true and the estimated activeness ($\Delta e_{ACT}$), and the mean absolute error of factor exposures (MAE).

We combine the estimation errors for our 3000 pseudo funds as well as the corresponding alphas. Then we sort the funds based on their estimation errors and divide them into quintiles. We then examine the difference of the alpha's between top and bottom quintiles. The results are shown in the Panel C of Table A1. Column 2 compares the alpha across groups based on MAE. The magnitude of mean alpha of each quintile is almost the same and the difference of mean alpha between Quintile 1 and Quintile 5 is virtually 0. The last two rows provide $p$ values for the $t$ test and the rank-sum test of Quintile 5 and Quintile 1, respectively. The high $p$ values indicate that the alpha's in Quintile 5 are not significantly different from those in Quintile 1. The other measure of estimation error is the difference between the true and the estimated activeness ($\Delta_{ACT}$). Sorting the pseudo funds into quintiles based on this measure, we find that the results are qualitatively the same the difference is not economically significant, though the $p$ values of the two statistical tests are lower.

**Table A1.** Simulation Results

This table presents simulation results. We construct time series of returns for three types of pseudo hedge funds which differ in the level of activeness in changing risk exposures. Type 1 funds are the most active ones while Type 3 funds are the least active. We conduct the simulation 1000 times. Panel A compares the calculated activeness, alpha, and $t$-statistics of alpha. Panel B tests the differences of these three variables across types of pseudo funds. Panel C examines the relation between alpha and estimation errors.

Panel A. Summary of Interested Measures

| | Activeness | | $\alpha$ | | $t_\alpha$ | |
|---|---|---|---|---|---|---|
| Pseudo Funds | $\mu$ | $\sigma$ | $\mu$ | $\sigma$ | $\mu$ | $\sigma$ |
| Type 1 | 0.0396 | 0.0158 | -0.0025 | 0.0040 | 0.0046 | 0.0945 |
| Type 2 | 0.0199 | 0.0080 | -0.0025 | 0.0022 | -0.0016 | 0.0907 |
| Type 3 | 0.0028 | 0.0019 | -0.0025 | 0.0007 | 0.0007 | 0.0715 |

Panel B. $p$-values of Tests

| | Activeness | | $\alpha$ | | $t_\alpha$ | |
|---|---|---|---|---|---|---|
| | $t$ test | ranksum test | $t$ test | ranksum test | $t$ test | ranksum test |
| Type 1 vs. 2 | 0.0000 | 0.0000 | 0.7448 | 0.9930 | 0.0929 | 0.1335 |
| Type 1 vs. 3 | 0.0000 | 0.0000 | 0.9650 | 0.6396 | 0.3002 | 0.2642 |
| Type 2 vs. 3 | 0.0000 | 0.0000 | 0.5695 | 0.2508 | 0.5230 | 0.3795 |

Panel C. $\alpha$ Sorted on the Estimation Errors

| | MAE | $\Delta e_{ACT}$ |
|---|---|---|
| Q1 | -0.0024 | -0.0025 |
| 2 | -0.0024 | -0.0025 |
| 3 | -0.0025 | -0.0025 |
| 4 | -0.0025 | -0.0026 |
| Q5 | -0.0024 | -0.0021 |
| Diff. 5 vs. 1 | 0.0000 | 0.0004 |
| $t$ test | 0.7847 | 0.0880 |
| ranksum test | 0.7955 | 0.1578 |

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