Returns to Active Management: the Case of Hedge Funds *

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Abstract

Do more active hedge fund managing strategies generate higher returns than the less active ones? We develop a novel approach to measuring activeness for hedge funds by estimating the dynamics of risk exposure of a large sample of live and dead equity long-short funds. We find that higher activeness is positively correlated with raw excess returns, but not with risk-adjusted returns. Furthermore, the relationship between risk-adjusted returns and activeness is likely non-linear and some specifications show evidence of a negative association. The results suggest that a strategy that exposes hedge funds to more frequent changes in market risk exposures comes at the expense of higher risks that are not necessarily justified by better performance.

Keywords: Hedge Funds, Fama-French, Active Management, Dynamic Trading

JEL classifications: G11, G12, G14, G23

*Much of this paper was written while Mazi Kazemi was with the Federal Reserve Board, thus, the views in this paper are solely the responsibility of the author(s) and should not be interpreted as reflecting the views of the Board of Governors of the Federal Reserve System or of any other person associated with the Federal Reserve System. Ergys Islamaj has been with the World Bank for part of this project. The views presented in this paper are those of the author(s) and do not necessarily reflect the views of the World Bank Group or World Bank Policy. We would like to thank the editor, Burton Hollifield, and an anonymous referee for their detailed feedback that has significantly improved the paper. We also thank Paul Ruud, Aurel Hizmo, Paul Johnson, John Rogers, Bo Sun, Mohammad Jahan-Parvar, participants at the Board of Governors research seminar, the MIT Sloan Finance Lunch, participants at GCER 2015 Biennial Conference for their many helpful comments. Any remaining errors are solely the responsibility of the authors.

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1 Introduction

This paper investigates whether more active hedge funds perform better than those which are less active in a large sample of 2,323 live and dead U.S. equity long-short hedge funds for the period 1994-2013.[1] Although the relationship between activeness and performance has been studied in the context of mutual funds (Huang, Sialm and Zhang, 2011; Cremers and Petajisto, 2009), there has been no systematic study analyzing activeness for hedge funds and its relationship with performance. We employ a Kalman Smoother procedure to estimate the risk exposure dynamics of each hedge fund, which are then used to create a fund-specific measure of activeness. Then, we run a battery of empirical tests to formally investigate the relationship between activeness and returns.

Since 1997, the hedge fund industry's assets under management (AUM) have increased by more than 22 times, with the AUM growing at an average pace of $135bn per year.[2] Hedge funds present themselves as absolute return investment vehicles, seeking to generate positive returns in any market condition. They can take long and short positions, can use leverage, and are not subject to the strict mandates that govern mutual funds. Further, hedge funds charge both management and incentive fees, where the incentive fees provide option-like returns to managers.[3] Given its loose investment mandate and fee structure, the hedge fund industry is expected to attract the most skilled asset managers.[4]

We propose a novel, intuitive approach to proxy for hedge fund activeness. We first estimate the dynamics of factor loadings on a standard benchmark model using the Kalman Smoother. Then, the time-varying estimates of risk exposures are used to construct a measure of activeness for each fund. Broadly speaking, factor loadings' dynamism can be achieved in two ways: (i) by a higher level of portfolio turnover and trading, or (ii) by investing in securities that have time-varying betas.[5] In that sense, activeness can be better understood as a feature of the fund's investment strategy, and not necessarily as an action on the part of the manager at a specific moment in time.

Next, we run an array of empirical tests to investigate whether activeness is robustly correlated with performance. When performance is measured by raw returns, we find a monotonic, positive relationship between activeness and performance. This observation is motivated by a non-parametric kernel and confirmed by cross-sectional regressions. When performance is measured by *risk-adjusted* returns, the relationship appears distinctly non-linear. The non-parametric results show a negative relationship between risk-adjusted returns and activeness, which turns positive only at the highest levels of activeness. Cross-sectional regressions of mean alpha on activeness even suggest a negative relationship between risk-adjusted returns and activeness, with the OLS coefficient estimate negative and statistically significantly different from zero. When allowing for the possibility of

[1] The terms manager and fund are used interchangeably throughout, and both refer to a specific investment fund, not the parent company, which may have multiple, differently managed funds.

[2] http://www.barclayhedge.com/research/indices/ghs/mum/Hedge_Fund.html

[3] In addition, most hedge fund managers have a significant portion of their personal wealth invested in the fund, aligning their interests with those of their investors even further.

[4] Incentive fees are typically 20% of a fund's profits above its previous high water mark. For instance, John Paulson, the founder of Paulson and Co, reportedly earned $5 billion in 2010. See http://www.forbes.com/pro.le/john-paulson/

[5] See Jagannathan and Wang (1996) for a discussion of time-varying stock betas in the CAPM setting.

a non-linear relationship, we also find a negative but not statistically significantly different from zero estimate. These observations would suggest that, if any, only a handful of active managers are successful in generating positive risk-adjusted returns for their funds. The non-parametric regression, which is known to be sensitive to extreme values and is a local measure of fit, suggests that a few very active managers are able to generate positive risk-adjusted returns. However, the cross-sectional results lead us to conclude that these managers make a statistically insignificant impact on the overall relationship between risk-adjusted returns and activeness, and that a more active hedge fund investment strategy is not associated with higher risk-adjusted returns.

A priori, it is not clear whether the after-fee performance of the more active funds should exceed those of the less active funds. Fund managers that have skills in the selection of securities may follow a buy-and-hold approach, while those who have skills in timing various segments of the market may follow a more active strategy. However, if both active and less active fund managers are equally skilled, or if markets are efficient, then, because of the transaction costs, we should expect to see lower performance on the part of the active managers.

Empirical studies of hedge funds' performance can be broken into two broad groups. One set of papers examines the empirical properties of the time-series of hedge fund returns and reports mixed results regarding hedge fund managers' abilities to generate abnormal risk-adjusted returns. In particular, recent studies tend to report very low or even negative risk-adjusted abnormal returns for hedge funds.[6]

The second group of papers focuses on the impact of funds' characteristics on their relative performance. The results show that characteristics such as size, age, location, uniqueness of strategy, delta of the incentive fee contract, level of co-investment by the manager and his/her level of education may be correlated with fund performance.[7] This paper adds to this strand of literature by reporting that cross-sectional differences in performance may be correlated with the extent of activeness of a fund's investment strategy.

The relationship between activeness and performance has been addressed by two recent papers in the case of mutual funds. These studies rely on reported security holdings.[8] Huang, Sialm,

[6]See, for example, Ackermann, McEnally, and Ravenscraft (1999), Brown, Goetzmann, and Ibbotson (1999), Agarwal and Naik (2000a, 2000b, 2000c, 2002), Capocci (2013), Edwards and Caglayan (2001), Asness, Krail, and Liew (2001), Fung and Hsieh (2000, 2001, 2004), Kao (2002), Liang (1999, 2000, 2001, 2003), Brown, Goetzmann, and Park (2000, 2001), Brown and Goetzmann (2003), Fung and Hsieh (1997, 2002, 2004), Lochoff (2002), Malkiel and Saha (2005), Ding and Shawky (2007), Kosowski, Naik, and Teo (2007), Fung, Hsieh, Naik, and Ramadorai (2008), Ibbotson, Chen, and Zhu (2011), and Cao, Chen, Liang, and Lo (2013).

[7]See, for example, Boyson (2008), Teo (2009), Agarwal, Daniel, and Naik (2009), Li, Zhang, and Zhao (2011), Titman and Tiu (2011), Gao and Huang (2012), and Sun, Wang, and Zheng (2012).

[8]In the U.S., fund management companies with assets under management exceeding \$100 million have to report their long holdings through quarterly filings known as 13f. While these filings provide some information about hedge funds' holdings, only long positions are reported and the holdings are reported at the company level rather than at the fund level. The anecdotal and academic evidence, at least for mutual funds' performance, is fairly clear. For example, in 2011, 84% of actively managed U.S. equity mutual funds underperformed their benchmarks. See Fama and French (2010), Wermers (2011), and http://www.prnewswire.com/news-releases/84-of-actively-managed-us-equity-funds-underperformed-their-benchmark-in-2011-57-trail-over-3-year-period-142356285.html.

and Zhang (2011) examine the relationship between risk-shifting and performance. They define activeness as the difference between a fund's prior returns variance (over the previous 36 months) and the variance of the current holdings (in the last 36 months). They report that mutual funds with more stable risk level tend to perform better. Cremers and Petajisto (2009) investigate the relationship between active share and performance. Active share is defined as the percentage of a mutual fund's holdings that does not overlap with that fund's stated benchmark portfolio. Their results also suggest that, for mutual funds, a higher active share is associated with higher returns.

This paper differs from the above studies in two ways. First, we study hedge funds, which as discussed before, are expected to attract the most talented traders. Second, we have to rely on reported monthly returns as opposed to asset holdings to measure how actively each fund is managed. It should be noted that the procedure developed in this paper can be applied to mutual funds as well.

More specifically, this paper uses a return-based approach to estimate exposure dynamics of our sample of hedge funds. Wermers (2011) warns of three potential problems when conducting return-based performance and risk exposure analysis. First, one must have an accurate measurement of the risk exposures of the managers by using appropriate benchmarks. Second, one must be aware of the difference between idiosyncratic and systematic risks in the fund's holdings. Finally, one should have a good understanding of the return distribution, which may deviate from the normal distribution.

We focus on hedge fund managers who invest in U.S. equity markets, and, therefore, we pick a model that reflects the equity risks they take (i.e., Fama-French-Carhart model). Second, by focusing on risk factors that have been shown to be correlated with cross-sectional differences in equity returns, we are able to differentiate between systematic and idiosyncratic risks. Finally, while it is assumed that hedge fund returns are normally distributed, we use robust standard errors in our analysis.

In order to study the time-series of hedge funds' risk exposures, we use a dynamic empirical model, as opposed to classical OLS, which estimates fixed betas on various risk-factors. Hasanhodzic and Lo (2007) employ multi-factor models with time varying coefficients to model trend-following strategies. The authors use rolling-window regressions to capture the dynamics of hedge funds' portfolio investment choices. As opposed to a constant-parameter regression, this methodology may offer further insights into the empirical properties of hedge fund returns. Still, there remains some ambiguity in choosing the optimal window size. In addition, a moving window approach is based on the assumption that coefficients are rather stable within each window.[9]

In contrast to Hasanhodzic and Lo (2007), we employ a Kalman Filter approach to estimate time-varying coefficients of risk-exposure for each hedge fund in the sample. Mamaysky, et al (2004) show that a dynamic regression using the Kalman Filter is better at explaining the time-series properties of mutual funds' returns and provides a more accurate out-of-sample forecast compared to static OLS models. In the case of hedge funds, Monarcha (2009) compares the explanatory power

[9]We also check the robustness of our results using time-varying risk exposure coefficients estimated using rolling window OLS regressions.

of a multi-factor model using a Kalman Filter with that of a static linear model.[10] In addition, Roncalli and Teiletche (2007) compare estimates of dynamic risk exposures obtained using the Kalman Filter to those obtained through a rolling window OLS approach. They find that the Kalman Filter produces smoother estimates of funds' factor loadings, and reacts to new information quicker than either the 12-month, the 24-month, or the 36-month rolling window techniques. Bollen and Whaley (2009) also use a dynamic regression with stochastic betas to measure risk-adjusted performance of hedge funds. They indicate that employing Kalman Filter to estimate risk exposures is an effective way to capture the time-dynamics of hedge fund allocations.

We contribute to the literature in two ways. First, we use the Kalman Smoother to create a novel measure to estimate the activeness of hedge fund investment strategies.[11] As we show below, this method has the convenience of only requiring knowledge of a fund's returns and a valid factor model. Second, we use our measure to explore cross-sectional relationships between activeness and performance

We start by presenting summary statistics for portfolios sorted on activeness to motivate further statistical analysis. Then, using both parametric and non-parametric regressions, we show there is a rich dynamic relationship between raw returns, risk-adjusted returns, and activeness. The rest of the paper is structured as follows. Section 2 formalizes the state-space representation of the model and discusses the activeness measure. Section 3 explain the data used. Section 4 shows the results and discusses robustness, while Section 5 offers some concluding remarks.

2 The Model

We estimate each hedge fund's exposures to market risk factors to create a benchmark for each manager.[12] Consider the general case of the excess return on a portfolio:

$$r_{p,t} - r_{f,t} = \sum_{i=1}^{n} w_{p,i,t-1}\left(r_{i,t} - r_{f,t}\right),\ p = 1, ..., K \tag{1}$$

In equation (1), $r_{p,t}$ is the return to hedge fund p at time t, $r_{f,t}$ is the risk-free rate at time t, $w_{p,i,t-1}$ is the loading on asset i decided at time period $t-1$, and $r_{i,t}$ is the time t return on asset i. The loading on risk-free rate in the portfolio is given by $(1 - \sum_{i=1}^{n} w_{p,i,t-1})$.

The expression above is an economic identity, as it describes how the excess return on a portfolio is equal to a weighted average of the excess returns of securities that constitute the portfolio. In practice, one does not know the exact composition of the portfolio for hedge funds, and thus the

[10]Using a sample of 6,716 funds with monthly data from January 2003 to December 2008, Monarcha (2009) finds that the mean adjusted R^2 rises from 0.60 for the static linear model to 0.72 for the dynamic case with the Kalman Filter.

[11]The Kalman Smoother is similar to the Filter. The former uses observations 1,...,T to estimate, say, β_t for $1 \leq t \leq T$.

[12]If the factors are in excess returns form, there is no need to impose a restriction that the weights have to add up to one. Further, since hedge funds can take long and short positions, there is no need to impose a non-negativity restriction on weights.

loadings have to be estimated using available returns on a set of asset classes or risk factors that approximate the investment universe considered by the portfolio manager. To that end, we employ the four-factor Fama-French-Carhart model (Fama and French (1992, 1993), Jegadeesh and Titman (1996), Carhart (1997)) to measure the risk exposures of each hedge fund.[13] These four factors have been shown to represent the sources of systematic risks of equity portfolios, and they represent excess returns on portfolios of available assets.[14]

The econometric representation of the model is:

$$r_{p,t} - r_{f,t} = \mathbf{w}_{p,t-1}^{'} \mathbf{f}_t + \varepsilon_{p,t}, \qquad p = 1, ..., K; \quad t = 1, .., T \tag{2}$$

where $\mathbf{w}_{p,t-1} = [w_{1,t-1}, ..., w_{5,t-1}]'$ is a 5×1 vector of loadings (i.e., the four market factor exposures and alpha), which will be estimated by the Kalman Smoother, $\mathbf{f}_t$ is a 5×1 vector of Fama-French-Carhart factors and the constant term, and error term is represented by $\varepsilon_{p,t}$. Note that while equation (1) is an economic identity, and, therefore, does not contain an error term, equation (2) contains an error term as it approximates the portfolio return process. The loadings are assumed to follow a random walk:

$$\mathbf{w}_{p,t} = \mathbf{w}_{p,t-1} + \mu_{p,t}, \qquad p = 1, ..., K, \quad t = 1, ..., T \tag{3}$$

where $\mu_{p,t}$ is a vector standard normal innovations.[15]

Once the parameters of equation (2) are estimated, we can then construct a measure of activeness for each fund based on the variations of the estimated values of $\mathbf{w}_{p,t}$. Activeness is defined as the sum of absolute changes in $\mathbf{w}_{p,i,t}$, where i refers to i^{th} market factor. That is,

$$\phi_p = \frac{1}{T_p} \sum_{i=1}^{4} \sum_{t=2}^{T_p} \left| w_{p,i,t} - w_{p,i,t-1} \right|. \qquad p = 1, ..., K \tag{4}$$

Here ϕ_p is defined as the measure of activeness of fund p.[16] Note that since our sample of hedge fund returns is unbalanced, the measure of activeness is adjusted by the length of the track record, T_p.

[13] Fung and Hsieh (2004) consider a seven factor model, which includes the market factor, the size factor, and two fixed-income factors. The other three factors represent returns to look-back options on three asset classes. The seven-factor model, in general, performs relatively well in explaining the time-series properties of hedge funds covering a wide set of strategies. However, these look-back options are meant to replicate returns from active trend-following strategies. As a result, it is unclear how one would interpret changes in exposures to these factors. Consequently, we use the four-factor model of Fama-French-Carhart, and interpret the changes in exposures in that model as an indication of active portfolio management. As mentioned earlier, this can be due to either the manager changing positions often, or choosing a portfolio of time-varying risk-exposures.

[14] For a description of all the risk-factors see: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

[15] We tried different persistence structure for $\mathbf{w}_{p,t}$ and got similar results.

[16] Alternatively, one could use the average standard deviation of the time-series of the estimated weights. We decided not to use this approach because it will not adequately capture the degree of activeness of a portfolio where the weights are trending in a predictable way

2.1 Discussion: Activeness

Before moving to the empirical estimation, a few caveats about our constructed measure of activeness should be discussed. Conceptually, our measure of activeness depends on changes in a fund's factor loadings from one period to the next. Ideally, one would want to directly measure each fund's exposure to every asset in the investment universe considered by the manager in each period. Given that this is impossible, we consider the four risk factors described above as proxies for the investment universe, and, thus, the changes in the loadings on those factors become proxies for the changing exposures.

However, the loadings on these factors may vary for two reasons. First, exposures can change because the manager is changing the composition of the fund's portfolio through trading. Second, exposures can change because the fund may invest in assets that have time-varying exposures. In this case, the fund manager is not actively trading, but has selected securities that display time-varying exposures. For example, a manager can earn the return on a derivative contract through dynamic trading or through the purchase of the derivative.[17] In other words, a portfolio may display time-varying exposures to factors through the active trading of the manager or through the deliberate purchase of securities that have time-varying exposures.[18]

Activeness, according to our definition, is driven by both of these factors. While it is impossible in practice to distinguish between the two, we take a pragmatic approach in this paper and regard activeness as a feature of the hedge fund's investment strategy. We take the view that the managers are aware that some of their holdings have time varying betas and, in that sense, activeness can be thought of as a trait of the fund's portfolio choice. While this assumption may not be valid for, say, a retail investor, it is not a stretch to assume that sophisticated hedge fund managers understand the return properties of their holdings. Therefore, we believe that our measure of activeness approximates a choice by the part of the manager to actively change their exposure to dynamic market risks.

3 Data and Summary Statistics

The data used is from the Center for International Securities and Derivatives at the University of Massachusetts-Amherst (CISDM). It includes 2,799 live and dead hedge funds whose Morningstar/CISDM category is listed as U.S. Long/Short Equity.[19] These funds primarily invest in U.S. equity markets, taking both long and short positions. The reported monthly returns are net of fees, calculated as the percentage change in the net asset value of each fund for the period June, 1994 to December, 2013.[20] We winsorize the data at the 2% level and eliminate all funds that had less than 18 consecutive months of data. Duplicate funds were removed from the sample.[21] This

[17] Agarwal and Naik (2000) show that hedge fund managers generate option-like returns on their portfolios.

[18] We thank an anonymous referee and Dobrislav Dobrev for helpful comments about this point.

[19] Since we include dead funds in our sample, the impact of survivorship bias should be somewhat mitigated.

[20] We drop the first five months of 1994 since the Kalman Smoother is less accurate for the initial months.

[21] Some funds appear multiple times under different fee structures.

leaves us with 2,352 funds.

Tables 1 and 2 present summary statistics for the returns of funds and the risk-factors, respectively. Figure 1 shows the number of funds in our sample over time. As expected, we see a large drop in the number of funds in the middle of 2007 as the financial crisis unfolded.

Tables 1 and 2 Here
Figure 1 Here

In this paper, the Fama-French-Carhart model will be the primary model used to explore the dynamics of hedge fund risk exposures. First, we present the results from static estimation of this model, which allows us to compare our preliminary results with those reported in the literature. We calculate OLS estimates of risk exposure using the following equation for each fund in the sample:

$$r_{p,t} - r_{f,t} = \alpha_p + w_{p,1}RMRF_t + w_{p,2}SMB_t + w_{p,3}HML_t + w_{p,4}UMD_t + \varepsilon_{p,t}. \tag{5}$$

where $r_{p,t}$ fund p's return, $r_{f,t}$ is the risk-free rate, $RMRF_t$ is the market excess return, SMB_t is the small cap over large cap excess return, HML_t is the value over growth excess return, UMD_t is the momentum factor, and $\varepsilon_{p,t}$ is the error term. The average of the estimated coefficients are presented in Table 3.

Table 3 Here

Note that most alphas are not significantly different from zero. In equation (5), the estimated mean abnormal return, α_p, is 0.2157% per month. Of all 2,352 funds, only 441 (18.75 percent) have statistically significantly positive alphas at the 5 percent significance level.[22] [23] Since we are considering long-short equity funds, it is not surprising that we find a high percentage of funds that have significant exposure to overall stock market risk ($RMRF$). In fact, this is the only risk factor that more than 80% of funds appear to have significant exposure to. Consistent with previous findings, the remaining results show that hedge funds tend to have positive exposures to the size factor, negative exposure to the value factor and positive exposure to the momentum factor (Capocci, 2013).

4 Results

4.1 Activeness and Returns: Basic Features

Next, we estimate the time-varying risk exposure coefficients in regression (5) using a Kalman Smoother methodology.[24] The time-series of the estimated coefficients of exposure to the four

[22] For alpha, we report the percentage of alphas with t-statistics greater than 1.96. For the Fama-French-Carhart factors, we report the percentage of coefficients with t-statistics whose absolute value is greater than 1.96.

[23] As noted Barras, Scaillet, and Wermers (2010), this process of looking at the percent of significant t-statistics suffers from a False Discovery Rate. Our presentation of these regressions is meant to only be suggestive motivation for our main tests.

[24] All empirical tests were carried out in MATLAB using the State Space Model toolbox developed by Peng and Aston (2011).

market factors for each fund is then used to create a measure of activeness for each manager as described in Section 2. Figure 2 displays the dynamics of the mean estimated loadings of the four factors for three different portolios of managers. Each subplot corresponds to one of the factors. The portfolios consist of managers in the upper and lower fifth percentile of activeness, that is, those that are more active than 95 percent of managers and those that are less active than 95 percent of managers, as well as the mean of the interquartile range. Confidence bands were constructed by generating 1000 factor loading time series for each percentile and selecting pointwise 95th percentiles. It can be seen that the weights are indeed time-varying, and that the differences in variation between the most and least active is large.[25]

Figure 2 Here

Table 4 presents summary statistics for excess returns and activeness for portfolios formed by the top (bottom) 5, 10 and 25 percentiles of the most (least) active funds. A t-test applied to difference in means between the top and bottom 5 percent most active funds shows that the average excess returns of the most active funds are statistically higher than those of the least active funds. In addition, the highly active funds' returns are more volatile than the returns of least active ones.

To examine differences in risk-adjusted returns of these different portfolios, Figure 3 displays the time-series of average alphas for three portfolios of managers: the top and bottom 5% of activeness and the interquartile range of activeness (the same portfolios as those graphed in Figure 2).[26] We see noticeable variation between these three series. This figure shows that risk-adjusted returns fluctuate more in the case of the most active managers, suggesting a possible relationship between activeness and alpha.

Table 4 Here
Figure 3 Here

4.2 Activeness and Returns: Regression Analysis

Next, we examine the relationship between activeness and performance for hedge funds using cross-sectional parametric and non-parametric regressions. We normalize the measure of activeness, ϕ_p, to create a measure of relative activeness:

$$\rho_p = \frac{\phi_p}{\bar{\phi}},$$

where $\bar{\phi}$ is the mean of activeness for the entire sample. Therefore, ρ_p shows how active fund p is relative to the average fund. A value of 1 would indicate that the fund is as active as the average fund of the sample. A larger (smaller) value means that the manager is more (less) active

[25] Variations on factor loadings over time, especially for the most active funds, are pronounced and can be interesting in and itself. This study focuses on the relationship between activeness and performance and leaves a detailed study of trends in factor loadings to future research.

[26] Confidence bands have been suppressed for clarity, but the differences are statistically significant for some time periods.

than average. Observing relative activeness, we notice that there are a handful of managers with extremely high levels of activeness (orders of three times the average activeness). We eliminate these outliers and consider only funds who have a value of ρ_p less than three.[27] As expected, a large number of managers are located around the mean (1 on the x-axis in the next figure), but there is a non-negligble number of managers located to the right and left. Figure 4 shows the distribution of ρ_p.

Figure 4 Here

After constructing the activeness measure, we begin our econometric tests with the non-parametric kernel regression. We present the results by plotting both the estimated functional relationships between alpha (risk-adjusted returns) and relative activeness and raw returns and relative activeness.[28] Figure 5 shows these relationships.[29]

Figure 5 Here

For the raw returns, we see that the pattern is almost monotonically increasing. The story with alpha is more complicated. Initially, for low to moderate levels of activeness, the relationship between activeness and risk-adjusted returns is negative. As activeness increases, the relationship between activeness and mean alpha turns flat with some notable fluctuations. Finally, for relatively high levels of activeness there is a noticeable positive relationship between activeness and mean alpha. Kernel regressions are sensitive at the end-points and are local measures of fit. We treat them as suggestive of a potential relationship between returns and activeness and use cross-sectional regressions to further examine the relationship between activeness and risk-adjusted returns.

Following these observations, we estimate the following regression:

$$Z_p = \sum_{n=0}^{2} \gamma_n \rho_p^n + \widetilde{u}_p, \qquad p = 1, .., K \tag{6}$$

where, Z_p represents the measure of performance of hedge fund p, ρ_p refers to relative activeness of the fund, and γ_n, for $n = 0, 1, 2$ refers to the coefficients that have to be estimated.[30]

[27] We are left with $2,323$ managers. The main findings remain unchanged when using a more stringent cut off.

[28] We thank an anonymous referee for this suggestion.

[29] To create confidence bands for the kernel regressions we use the following procedure. [See Sun, Jiayang and Clive Loader (1994) and the references therein]. Let $f(x)$ denote the function we wish to estimate relating activeness, x, to a measure of performance. Call the non-parametric estimate $\hat{f}(x)$. Let

$$Z_i = \log\left(Y_i - \hat{f}(x_i)\right)^2.$$

where Y_i is observed data point of performance. Call the non-parametric estimate of Z as a function of x, $\hat{q}(x)$. Then,

$$\hat{\sigma}^2(x) = e^{\hat{q}(x)}.$$

Therefore, $\hat{\sigma}^2(x)$ is a pointwise measure of the variance which we use to construct confidence bands around $\hat{f}(x)$. The bands are indeed wider at the end-points.

[30] Following the observations from the kernel regression estimates we test for both a linear and quadratic relationship between returns and activeness.

Next, we show the results from cross-sectional regressions analyzing the relationship between the constructed measure of activeness and returns. First, we run regression equation (6) using mean excess returns of each fund as the dependent variable. In all regression estimates, we use robust standard errors. Since we have to statistically estimate the value of ρ_p which appears in equation (6), we have a classical errors-in-variables problem. The Appendix explains how we multiply our estimated betas and t-statistics by an adjustment matrix to correct for the errors. Table 5 presents the results of regressing raw returns on activeness.

Table 5 Here

Column (a) contains results from the regression without including activeness squared. These cross-sectional estimates suggest that higher raw excess returns are positively correlated with higher activeness. The coefficient is positive and statistically significantly different from zero. This would suggest that the managers who have more dynamic factor loadings are also the ones that generate higher raw returns. In column (b), when we include the square of activeness, we continue to see positive returns to activeness.

However, these higher raw returns may come at the cost of taking on more risk, leading to lower risk-adjusted returns.[31] To explore the possibility that higher risk taking by the more active managers is driving higher raw returns, we re-estimate equation (6), using each fund's alpha as dependent variable. Alpha refers to the average value of the intercept in equation (5) with the factor exposures estimated using the Kalman Smoother. The results of estimating equation (6) when $Z_p = \alpha_p$ are presented in Table 6.

Table 6 Here

Column (a) presents results when average alpha is regressed on activeness, and column (b) adds activeness squared as a regressor. The regression results in column (a) indicate that there is a decreasing relationship between risk-adjusted returns and activeness.[32] The results in column (b) show that once we include activeness squared, though both regressors have negative coefficients, neither is statistically significantly different from zero.[33] Since more active trading generates more fees that the investors must pay, a statistically insignificant relationship between activeness and mean alpha indicates that any excess returns generated by the managers may be offset by the fees they charge. Looking at the kernel regression estimates, at best, there is only a handful of highly active managers who are able to generate positive risk-adjusted returns. However, the overall relationship between activeness and risk-adjusted returns is not different from zero when one considers a non-linear relationship structure.

[31]A note must be made of the very low R^2 coefficients in our regressions. This is not surprising, given that hedge fund returns depend on many factors. As long as these factors are not strongly correlated with activeness, our coefficient estimates are accurate. A likely candidate would be AUM for each fund. We found that there is no clear relationship between size and activeness. The correlation is only 0.049.

[32]This confirms the initial downward trend in the non-parametric kernel in Figure 5.

[33]We refer to column (b) as our preferred specification following the suggested non-linear relationship between activeness and mean alpha by the kernel regression in Figure 5.

Next, we conduct a number of robustness exercises. First, we analyze the relationship between activeness and performance for live and dead funds separately. A fund is considered dead if it has no returns data in our database for the last 24 months. A fund is considered live if it has reported returns for the last 24 months in our database. This leaves us with 1,153 dead funds and 836 live funds. Table 7 presents the results for live funds and Table 8 presents results for dead funds.

Table 7 Here

Table 8 Here

For both groups, activeness appears to be associated with higher raw returns, but not higher risk-adjusted returns, consistent with our baseline estimates.

So far, the dynamic loadings used to construct our measure of activeness are the betas from the four factor model. In theory, any set of portfolios that are a reasonable proxy for the investment universe of the fund managers can be used to produce similar measures of activeness, and hence, similar results. As further robustness checks, we use the 10 industry portfolios on Kenneth French's website to generate an equivalent measure of activeness. We then re-estimate equation (6) using a measure of activeness that is constructed by time-varying industry exposure portfolios, as opposed to the standard market benchmarks.[34] The results, presented in Table 9, are similar to our earlier findings.[35] The main difference appears in column (b) for raw returns, suggesting a statistically insignificant relationship between raw returns and activeness. The estimates from the mean alpha regressions are similar to the baseline. We interpret these results as further evidence that adds credence to the claim that activeness does not improve performance.

Table 9 Here

As a final robustness check, we use rolling window OLS regressions, as an alternative to Kalman Smoother regressions, to generate time varying betas and re-estimate (6). We use a window size of 24 months. The results are presented in Table 10. As we discussed earlier, the larger the window size, the harder it becomes to capture intra-window beta dynamics. Therefore, we have chosen as small a window as feasible. The results are again in line with our main regressions, with activeness not robustly correlated with risk-adjusted returns. The third column shows an estimated coefficient of regression risk-adjusted returns on activeness very close to zero. The estimated coefficients effect appear to be negative and not statistically different from zero when including activeness squared as a regressor, our preferred specification, and suggest that higher activeness is not robustly correlated with higher risk-adjusted returns.

Table 10 Here

[34] Note that we are using portfolios of stocks now, rather than risk-factors. Of course, risk-factors are a specific set portfolios. We use estimates of alpha from the original four-factor model. This is necessary since there is no evidence that the 10 industry portfolios are priced risk factors that capture the systematic risks of a portfolio. Any "alpha" computed from the industry regression will not necessarily be equivalent to Jensen's alpha.

[35] The regression includes all live and dead funds in our sample.

4.3 Discussion

Why would hedge funds pick a strategy that increases their activeness towards risk if there are no gains (in their risk-adjusted returns) by doing so? One explanation might be that investors focus more on raw returns and not on risk-adjusted returns. Second, the fund manager may not realize ex-ante that increased activeness will not increase the risk-adjusted return. Third, some studies suggest that some hedge fund managers may trade not because it may lead to better performance but rather because it may increase fund inflows and thus the fund manager's income.[36] Fourth, because fund managers earn performance fees based on raw returns, managers will have the incentive to increase the raw return even though it may reduce the risk-adjusted return as long as it does not reduce fund inflows.

While managers may have the incentives to engage in activities that increase raw returns and do not affect risk-adjusted returns, it is not immediately clear why investors continue to invest in these funds. One possibility, as mentioned above, is that investors care about raw returns and not the risk-adjusted ones. Second, liquidating a current hedge fund position and finding a new manager is costly and therefore, as long as the fund generates positive returns, it may be optimal not to liquidate the position.[37]

One direction for future research is to apply these results to truly dead funds; that is, funds that stopped reporting to a database because they went out of business. Also, the methodology developed in this paper can be applied to any number of investment vehicles for which valid risk-factor models describing their investment universes exist (e.g., mutual funds, international hedge funds, non-equity hedge funds, etc.).

5 Conclusions

Hedge funds vary widely in terms of how frequently they change their exposure to different market risks. Do more hedge funds that have picked a strategy that actively changes their exposure to market risk factors perform better than their less active peers? We use a Kalman Smoother approach to estimate time-varying market risk exposures for a sample of 2,323 U.S. equity long-short hedge fund for the period June, 1994 to December, 2013. The dynamic estimates are then used to construct a measure of activeness for each fund. Using an array of empirical tests, we analyze whether the funds that change their exposure to market risks more often are able to generate higher returns.

We find that more active funds generate higher raw returns compared to their less active peers. To discern whether this is a product of smarter management or more risk taking, we also analyze the relationship between activeness and risk-adjusted returns. Our results suggest that, in terms of risk-adjusted returns, activeness does not improve performance. Only a handful of highly active managers may be able to overcome the higher transaction cost and generate higher risk-adjusted

[36] See for example Brown et al. (2005) and Agarwal, Gay and Ling (2014).

[37] See Brown, Fraser and Liang (2008).

returns.

Our study is the first one to investigate the relationship between active management and returns for hedge funds, and should provide a benchmark to future studies on the subject. The results presented here point to at least three area of research. First, it would be useful to investigate further how hedge funds choose between risks and raw returns. Second, future research should investigate whether activeness is correlated with other fund characteristics. Finally, our findings suggest nonlinearities in the relationship between activeness and risk-adjusted returns. It would be interesting to focus more on the few most active funds that are able to generate higher risk-adjusted returns when compared to their peers and to understand better the nature of these nonlinearities.

6 Appendix: Monte Carlo Measurement Error Correction

One potential problem that arises when estimating the cross-sectional regression (6) is that the explanatory variables ϕ_p and ϕ_p^2 are estimates of the true measure of activeness, and, therefore, regression (6) suffers from errors-in-variables. We apply a Monte Carlo procedure to obtain estimates of the magnitudes of the measurement errors, which are then used to adjust the estimated values of γ_1 and γ_2. The details of the Monte Carlo procedure and the resulting correction are described here.

Assume the following cross-sectional regression specification,

$$Y = X\beta + \varepsilon$$

where ε is a white noise process. In our case, X is data on each manager's estimated measure of activeness. Our measure of activeness is the sum, over time, of changes in each manager's exposure to market risk factors, estimated via a Kalman Smoother in a state-space setting. We will assume that these data suffer from classical measurement error. That is, we actually observe,

$$W = X + u$$

where $Cov\left(u, X\right) = Cov\left(u, Y\right) = Cov\left(u, \varepsilon\right) = 0$. As we know, the OLS estimate of β would be $\left(X'X\right)^{-1} X'Y$. However, using OLS in our case would produce,

$$\hat{\beta}_{EST} = \left(W'W\right)^{-1} W'Y.$$

Notice that (asymptotically),

$$W'Y = \left(X' + u'\right) Y = X'Y + u'Y = X'Y.$$

Thus,

$$\left(X'X\right)^{-1} \left(W'W\right) \hat{\beta}_{EST} = \left(X'X\right)^{-1} \left(W'W\right) \left(W'W\right)^{-1} X'Y = \left(X'X\right)^{-1} X'Y = \hat{\beta}_{OLS}.$$

We do not know $X'X$, but if we had a measure of $u'u$ we could estimate it as $W'W - u'u$. Note that these results hold asymptotically. The ideal "adjustment matrix" we suggest is the probability limit of the one we construct.

$$ADJ = plim_{n\to\infty, p\to\infty} \left(W'W/n - u'u/p\right)^{-1} \left(W'W/n\right)$$

where n is the sample size and p is the number of simulations (see below).

To achieve this, we run a Monte Carlo simulation. We initialize a fictional manager's loadings to be the mean loadings from our actual data. We then make time t loading equal to time $t-1$ loading plus a standard normal random disturbance, just as in equation (3). Then, using the Fama-French-Carhart factors, we compute the corresponding returns from these loadings. That is, let $\mathbf{w}$ denote the Tx5 matrix of generated weights. Then the the returns generated from the fictional loadings at each time t are:

$$R_t = \mathbf{w}_t \cdot [1, \text{Fama-French Factors}_t]$$

where $\mathbf{w}_t$ is the tth row of $\mathbf{w}$ and $\cdot$ is the inner-product operator. We subject this manager's returns to the same Kalman Smoothing technique as in the main body of this paper. We compare the smoother's estimates to the "true" loadings and call the difference u_i, for $i = 1, ..., 1000$. The matrix of differences is our stand-in for u. This is a 1000x3 matrix.[38] Thus, we correct our betas as,

$$A\hat{D}J * \hat{\beta}_{EST}, \text{ where } A\hat{D}J = \left(W'W/n - u'u/p\right)^{-1}\left(W'W/n\right)\big) = \begin{pmatrix} 1 & 1.0388 & 1.1312 \\ 0 & -0.8562 & -2.0235 \\ 0 & -0.6592 & 1.7197 \end{pmatrix}.$$

Since both n and p are large, we believe asymptotic results will approximately hold.

Our estimation method in the main body of the paper has the flavor of Fama and MacBeth (1973). The biggest difference being that their first stage time series regressions produce one beta (loading, in our case) over the sample, whereas we estimate a different beta (loading) for each t in the sample.

[38] The first column is all zeros, since the constant is measured with zero error.

References

[1] Ackermann, Carl, McEnally, Mark, and David Ravenscraft. 1999. "The Performance of Hedge Funds: Risk, Return, and Incentives". *Journal of Finance.* 54(3), 833-874

[2] Agarwal, Vikas, Gay, Gerald D., and Leng Ling. 2014. "Window Dressing in Mutual Funds". *Review of Financial Studies.* 27(11), 3133-3170

[3] Agarwal, Vikas and Narayan Y. Naik. 2000a. "Generalized Style Analysis of Hedge Funds". *Journal of Asset Management.* 1, 93-109

[4] Agarwal, Vikas and Narayan Y. Naik. 2000b. "Multi-Period Performance Persistence Analysis of Hedge Funds". *Journal of Financial and Quantitative Analysis.* 35, 327-342

[5] Agarwal, Vikas and Narayan Y, Naik. 2000c. "On Taking the Alternative Route: Risk, Rewards, and Performance Persistence of Hedge Funds". *Journal of Alternative Investments.* 2(4), 6-23

[6] Agarwal, Vikas and Narayan Y. Naik. 2002. "Determinants of Money-Flow and Risk-Taking Behavior in the Hedge Fund Industry". *Working Paper, Georgia State University*

[7] Asness, Clifford, Krail, Robert, and Liew, John. 2001. "Do Hedge Funds Hedge?". *Journal of Portfolio Management*, 28(1), 6-20

[8] Barras, Laurent, Scaillet, Olivier, and Russ Wermers. 2010. "False Discoveries in Mutual Fund Performance: Measuring Luck in Estimated Alphas". *Journal of Finance*, 65(1)

[9] Bollen, Nicholas P. B., and Robert E. Whaley. 2009. "Hedge Fund Risk Dynamics: Implications for Performance Appraisal." *Journal of Finance*, 64(2), 985-1035

[10] Brown, Stephen J., Fraser, Thomas, and Bing Liang. 2008. "Hedge Fund Due Diligence: A Source of Alpha in a Hedge Fund Portfolio Strategy". *Journal of Investment Management.* 6(4), 23-33

[11] Brown, Stephen J. and William N. Goetzmann. 2003. "Hedge Funds with Style". *Journal of Portfolio Management.* 29, 101-112

[12] Brown, Stephen J., Goetzmann, William N., and J. Park. 2001. "Careers and Survival: Competition and Risk in the Hedge Fund and CTA Industry". *Journal of Finance.* 56, 1869-1886

[13] Brown, Stephen J., Goetzmann, William N., and J. Park. 2000. "Hedge Funds and the Asian Currency Crisis". *Journal of Portfolio Management.* 26(4), 95-101

[14] Brown, Stephen J., Goetzmann, William N., and Roger G. Ibbotson. 1999. "Offshore Hedge Funds: Survival & Performance 1989-1995". *Yale Working Paper Series*

[15] Brown, Stephen J., Swan, Peter L., Steenbeek, Onno W., and David R. Gallagher. 2005. "Double or Nothing: Patterns of Equity Fund Holdings and Transactions". *EFA 2005 Moscow Meetings Paper*

[16] Capocci, Daniel P. J. 2013, "The Complete Guide to Hedge Funds and Hedge Fund Strategies," Palgrave Macmillan.

[17] Cao, C., Chen, Y., Liang, B., and A. Lo. 2013. "Can Hedge Funds Time Market Liquidity?". *Journal of Financial Economics.* 109(2), 493-516

[18] Carhart, Mark M. 1997. "On Persistence in Mutual Fund Performance". *Journal of Finance*, 52(1), 57-82

[19] Cremers, K. J. Martijn, and Antti Petajisto. 2009. "How Active Is Your Fund Manager? A New Measure that Predicts Performance". *The Review of Financial Studies.* 22(9), 3329-3365

[20] Ding, Bill, and Hany A. Shawky. 2007. "The Performance of Hedge Fund Strategies and the Asymmetry of Return Distributions". *European Financial Management.* 13(2), 309-331

[21] Edwards, Franklin, and M. Caglayan. 2001. "Hedge Fund Performance and Manager Skill". *Journal of Futures Market.* 21(11), 1001-1028

[22] Fama, Eugene F., and Kenneth R. French. 1992. "The Cross-Section of Expected Stock Returns". *Journal of Finance.* 47(2), 427-465

[23] Fama, Eugene F., and Kenneth R. French. 1993. "Common Risk Factors in the Returns on Stocks and Bonds". *Journal of Financial Economics.* 33(1), 3-56

[24] Fama, Eugene F., and Kenneth R. French. 1996. "Multifactor Explanations of Asset Pricing Anomalies". *Journal of Finance.* 51(1), 55-84

[25] Fama, Eugene F., and Kenneth R. French. 2010. "Luck Versus Skill in the Cross Section of Mutual Fund Returns." *Journal of Finance.* 65(5), 1915-1947

[26] Fama, Eugene F., and James D. MacBeth. 1973. "Risk, Return, and Equilibrium: Empirical Tests." *Journal of Political Economy.* 81(3), 607-636

[27] Fung, William, and David A. Hsieh. 2002. "Asset-Based Style Factors for Hedge Funds". *Financial Analysts Journal.* 58(5), 16-27

[28] Fung, William, and David A. Hsieh. 1997. "Empirical Characteristics of Dynamic Trading Strategies: The Case of Hedge Funds". *Review of Financial Studies.* 10, 275-302

[29] Fung, William and David A. Hsieh. 2000. "Performance Characteristics of Hedge Funds and CTA Funds: Natural Versus Spurious Biases". *Journal of Financial and Quantitative Analysis.* 35, 291-307

[30] Fung, William, and David A. Hsieh. 2001. "The Risk in Hedge Fund Strategies: Theory and Evidence from Trend Followers". *The Review of Financial Studies*. 14(2), 313-341

[31] Fung, William, and David A. Hsieh. 2004. "Hedge Fund Benchmarks: A Risk-Based Approach". *Financial Analysts Journal*. 60(5), 65-80

[32] Fung, William, Hsieh, David A., Naik, N., and T. Ramadorai. 2008. "Hedge Funds, Performance, Risk, and Capital Formation". *Journal of Finance*. 64. 1777-1803.

[33] Hasanhodzic, Jasmina, and Andrew W. Lo. 2007. "Can Hedge-Fund Returns Be Replicated?: The Linear Case". Can Hedge-Fund Returns Be Replicated?: The Linear Case" *Journal of Investment Management*, Vol. 5, No. 2, pp. 5-45

[34] Greene, William H. 2011, *Econometric Analysis*, Prentice-Hall, New York.

[35] Huang, Jennifer, Sialm, Clemens, and Hanjiang Zhang. 2011. "Risk Shifting and Mutual Fund Performance". *The Review of Financial Studies*. 24(8), 2575-2616

[36] Ibbotson, R.G., Chen, P., and K. X. Zhu. 2011. "The ABCs of Hedge Funds: Alphas, Betas, and Costs". *Financial Analysts Journal*. 67, 15-25

[37] Jagannathan, Ravi, and Zhenyu Wang. 1996. "The Conditional CAPM and the Cross-Section of Expected Returns". *Journal of Finance,* Vol. 51, No. 1, pp. 3-53

[38] Jegadeesh, Narasimhan, and Sheridan Titman. 1993. "Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency". *Journal of Finance*. 48(1), 65-91

[39] Kao, D. 2002. "Battle for Alphas: Hedge Funds Versus Long-Only Portfolios". *Financial Analysts Journal*. 58(2), 16-34

[40] Kosowski, R., Naik, N., and M. Teo. 2007. "Do Hedge Funds Deliver Alpha? A Bayesian and Bootstrap Analysis". *Journal of Financial and Quantitative Analysis*. 31, 3291-3310

[41] Liang, Bing. 1999. "On the Performance of Hedge Funds". *Financial Analysts Journal*. 55, 72-85

[42] Liang, Bing. 2000. "Hedge Funds: The Living and the Dead". *Journal of Financial and Quantitative Analysis*. 35, 309-326

[43] Liang, Bing. 2001. "Hedge Fund Performance: 1990-1999". *Financial Analysts Journal*. 57, 11-18

[44] Liang, Bing. 2003. "The Accuracy of Hedge Fund Returns". *Journal of Portfolio Management*. 29, 111-122

[45] Lochoff, R.W. 2002. "Hedge Funds and Hope". *Journal of Portfolio Management*. 28(4), 92-99.

[46] Malkiel, B. and A. Saha. 2005. "Hedge Funds: Risk and Return". *Financial Analysts Journal*. 61. 80-88

[47] Mamaysky, H.,Spiegel, M., and H. Zhang. 2004, "Estimating the Dynamics of Mutual Fund Alphas and Betas". *Yale IFC Working Paper*

[48] Monarcha, Guillaume. 2009. "A Dynamic Style Analysis Model for Hedge Funds". *Orion Financial Partners Working Paper Series*

[49] Peng, Jyh-Ying, and John A. D. Ashton. 2011. "The State Space Models Toolbox for MATLAB". *Journal of Statistical Software*, 41(6)

[50] Roncalli, Thierry, and Jerome Teiletche. 2007. "An Alternative Approach to Alternative Beta". *Working Paper Series*

[51] Sharpe, William F. 1994, "Sharpe Ratio," *The Journal of Portfolio Management,* 21(1).

[52] Sun, Jiayang and Clive Loader, "Simultaneous Confidence Bands for Linear Regression and Smoothing" *The Annals of Statistics*1994, 22 (3)

[53] Wermers, Russ. 2011. "Performance Measurement of Mutual Funds, Hedge Funds, and Institutional Accounts". *Annual Review of Financial Economics*, 3, 537-574

Table 1: Summary Statistics for Manager Returns

	Mean	Max	Min
Average	0.4725	2.0456	-0.6300
Standard Deviation	3.9437	14.3734	0.1661
Skewness	-0.3305	6.7555	-12.6061

The sample contains 2,323 funds for the period from June, 1994 to December, 2013.

Table 2: Summary Statistics for Fama-French-Carhart Factors

	RMRF	SMB	HML	UMD
Mean	0.6460	0.2233	0.2213	0.4877
Standard Deviation	4.5491	3.4718	3.2973	5.3403
Max	11.3400	22.0200	13.8700	18.3900
Min	-17.2300	-16.3900	-12.6800	-34.7200
Skewness	-0.7492	0.8604	0.0395	-1.5917

The statistics are computed for each factor over the time period 1994-2013.

Table 3: Static OLS of Equation (5)

Variable	Mean Coefficient Value	% of t-stats sig. at 5%
Constant	0.2157	18.75
RMRF	0.4803	0.8197
SMB	0.0354	0.2160
HML	-0.0311	0.1212
UMD	0.0483	0.3176
% F-stat sig. at 5% level	88.78	
Average R^2	0.3850	

Column one shows unweighted averages of OLS regression estimates for each of 2,352 funds in our sample. The second column shows (# t-stats significant at 5%)/2,352. For the constant (i.e., alpha), we report only the % of t-statistics that are positively significant. The second to last row is computed analogously to the t-statistics, and the final row is the average R^2 across all the regressions.

Table 4: Summary Statistics for Activeness-Sorted Portfolios

	Top 25%	Top 10%	Top 5%
Mean Excess Return	0.6441	0.7623	0.8262
Mean Standard Deviation	6.0318	7.3009	8.3990
Mean Skewness	-0.2116	-0.0789	-0.0536
Mean Kurtosis	6.2072	6.3494	6.6716
Mean Activeness	1.5938	1.9517	2.2339
Standard Deviation of Activeness	0.3813	0.3599	0.2917
	Bottom 25%	Bottom 10%	Bottom 5%
Mean Excess Return	0.3351	0.3123	0.3131
Mean Standard Deviation	2.0824	1.6785	1.4829
Mean Skewness	-0.4679	-0.5871	-0.5224
Mean Kurtosis	6.7162	7.3457	7.4771
Mean Activeness	0.4305	0.3272	0.2737
Standard Deviation of Activeness	0.1036	0.0721	0.0647

Funds are sorted based on the activeness of their portfolios over the sample period June, 1994 to December, 2013. Mean statistics for each top (bottom) percentile refers to the unweighted average of all the statistics for the funds above (below) that threshold after sorting activeness in ascending order. Standard deviation is computed analogously.

Table 5: Equation (6) for Mean Excess Returns

	(a)	(b)
Constant	0.2155	0.2618
	(9.5362)	(7.9475)
Activeness	0.2674	0.1263
	(11.8298)	(3.8348)
Activeness Squared		0.0776
		(2.3576)
R^2	0.0765	0.0769
F-Stat	192.4897	193.5678

This table presents the results of running OLS on equation (6) when the dependent variable is Mean Excess Returns. All the coefficients and t-statistics, in parentheses, have been corrected by the adjustment matrix described in the Appendix.

Table 6: Equation (6) for Mean Alpha

	(a)	(b)
Constant	0.1228	0.0795
	(3.2214)	(1.2770)
Activeness	-0.1455	-0.0573
	(-3.8172)	(-0.9211)
Activeness Squared		-0.0360
		(–0.5784)
R^2	0.0120	0.0189
F-Stat	28.1483	44.6974

This table presents the results of running OLS on equation (6) when the dependent variable is Mean Alpha. All the coefficients and t-statistics, in parentheses, have been corrected by the adjustment matrix described in the Appendix.

Table 7: Equation (6) for Live Funds

	Mean Excess Returns		Mean Alpha	
	(a)	(b)	(a)	(b)
Constant	0.3930	0.4468	0.3447	0.2918
	(12.7044)	(9.6921)	(5.5337)	(3.5751)
Activeness	0.2820	0.1298	-0.3590	-0.1747
	(9.1182)	(2.8164)	(-5.7625)	(-2.1407)
Activeness Squared		0.0816		-0.1095
		(1.7694)		(-1.3416)
R^2	0.0985	0.0991	0.0637	0.0666
F-Stat	91.3553	91.9132	56.8770	59.6335

This table presents the results of running OLS on equation (6) for Live funds. See text for details. All the coefficients and t-statistics, in parentheses, have been corrected by the adjustment matrix described in the Appendix.

Table 8: Equation (6) for Dead Funds

	Mean Excess Returns		Mean Alpha	
	(a)	(b)	(a)	(b)
Constant	0.1293	0.1632	0.0421	0.0222
	(3.8191)	(3.1732)	(0.9523)	(0.3213)
Activeness	0.2429	0.1203	-0.0149	0.0037
	(7.1777)	(2.3399)	(-0.3364)	(0.0531)
Activeness Squared		0.0722		0.0019
		(1.4031)		(0.0274)
R^2	0.0638	0.0691	0.0002	0.0123
F-Stat	78.5146	85.6505	0.1924	14.4042

This table presents the results of running OLS on equation (6) for Dead funds. See text for details. All the coefficients and t-statistics, in parentheses, have been corrected by the adjustment matrix described in the Appendix.

Table 9: Equation (6) for 10 Fama-French Industry Portfolios

	Mean Excess Returns		Mean Alpha	
	(a)	(b)	(a)	(b)
Constant	0.2178	0.5251	0.1250	-0.0471
	(9.0705)	(14.6473)	(3.2386)	(-0.7094)
Activeness	0.2642	-0.0384	-0.1473	0.0220
	(11.0018)	(-1.073)	(-3.8164)	(0.3311)
Activeness Squared		-0.0134		0.0076
		(-0.3726)		(0.1150)
R^2	0.0744	0.0748	0.0122	0.0155
F-Stat	186.6312	187.7815	28.7290	36.6661

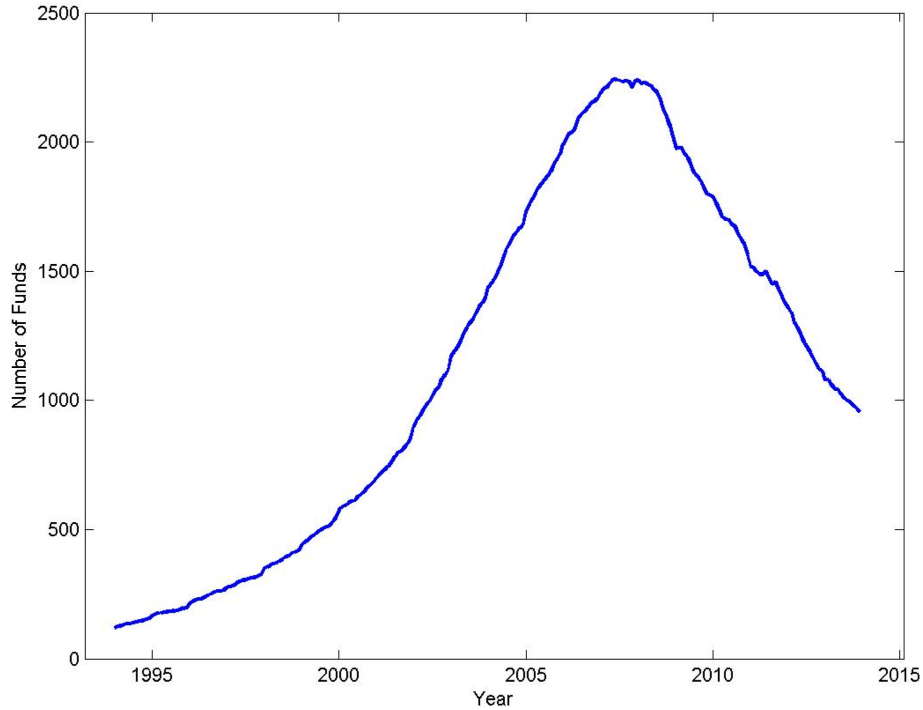
This table presents the results of running OLS on equation (6) where activeness is computed using the 10 Fama-French Industry Portfolios as factors in the Kalman Smoother. All the coefficients and t-statistics, in parentheses, have been corrected by the adjustment matrix described in the Appendix. The mean alpha we use as our dependent variable is from our original specification with the Fama-French-Carhart factors.

Table 10: Equation (6) for 24 Month Rolling Window

	Mean Excess Returns		Mean Alpha	
	(a)	(b)	(a)	(b)
Constant	0.1357	0.5622	0.0370	0.1622
	(7.7458)	(13.2996)	(1.5628)	(6.5867)
Activeness	0.3252	-0.1398	0.0976	-0.0384
	(18.5674)	(-3.3069)	(4.1242)	(-1.5612)
Activeness Squared		0.0162		0.0045
		(0.3833)		(0.1808)
R^2	0.1503	0.1522	0.0134	0.0174
F-Stat	410.3094	416.4433	31.5995	41.1485

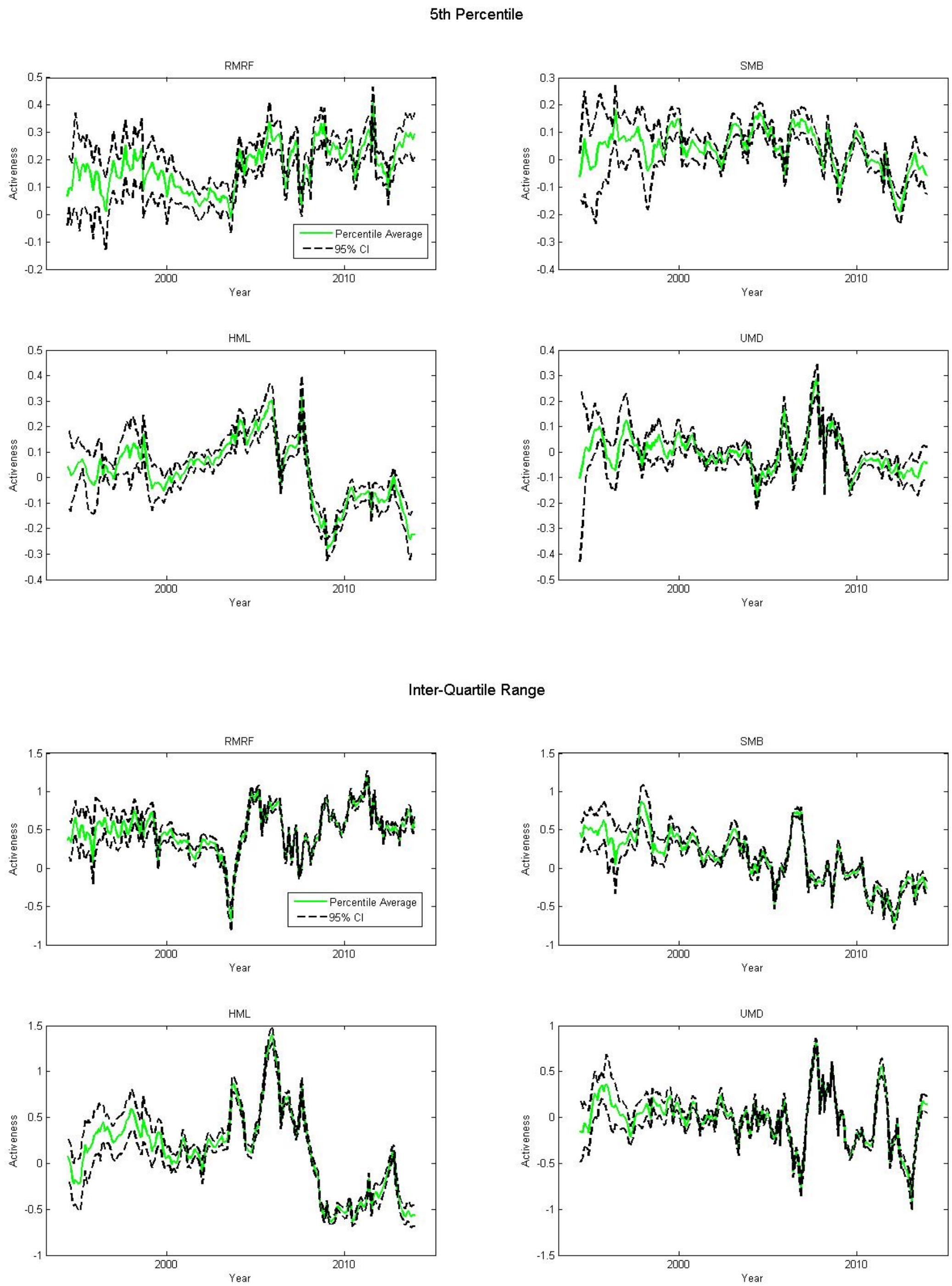
This table presents the results of running OLS on equation (6) where activeness is computed using a 24 month rolling window over the Fama-French-Carhart factors. All the coefficients and t-statistics, in parentheses, have been corrected by the adjustment matrix described in the Appendix.

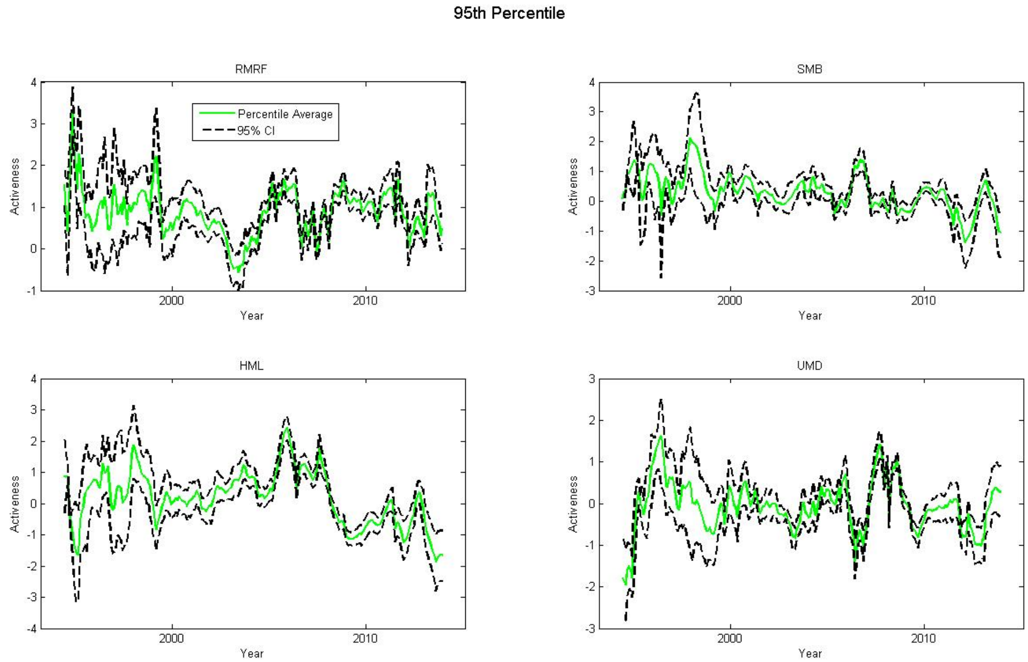
Figure 1: Number of Hedge Funds Reporting Returns



This figure displays the number of funds reporting returns for each month in our sample.

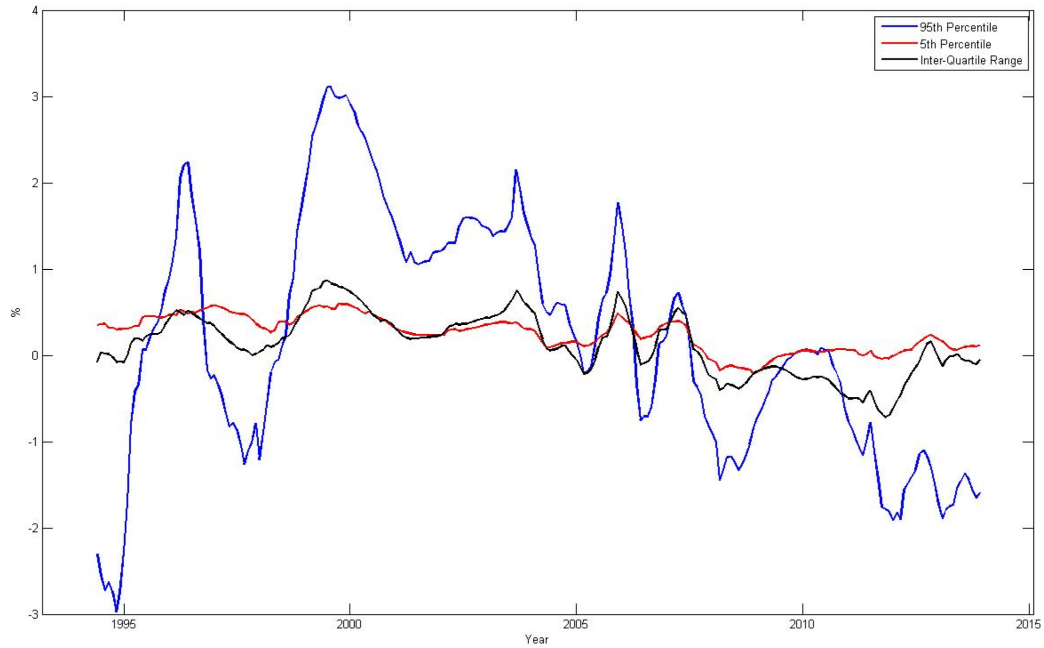
Figure 2: Time Series Evolution of Factor Loadings





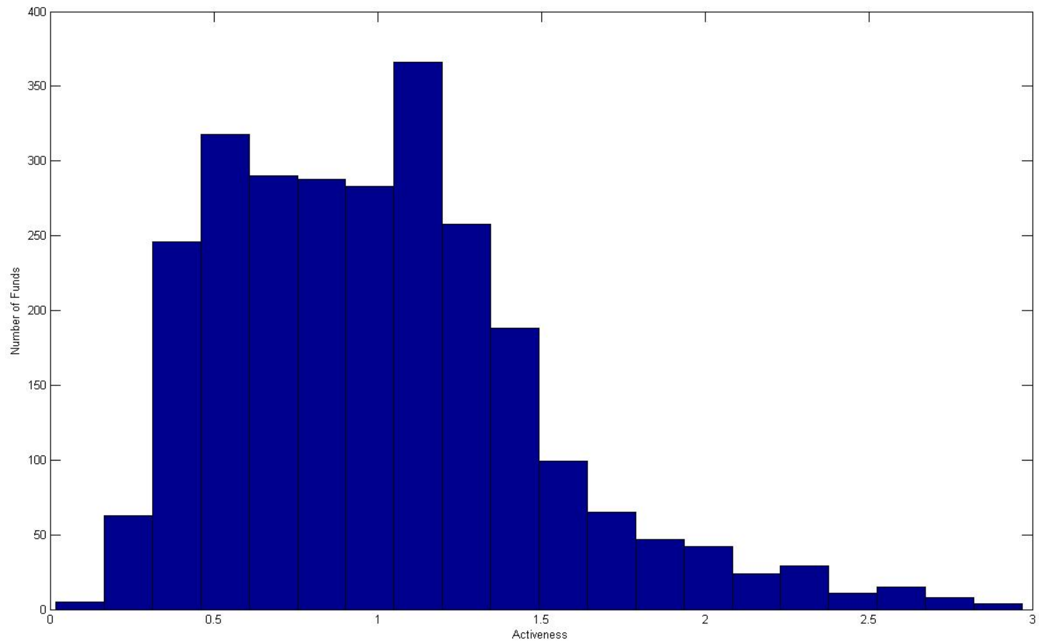
This figure displays the time series evolution of factor loadings for firms at or below the 5th percentile of activeness, the interquartile range, and those at or above the 95th percentile of activeness. The 95 percent pointwise confidence interval is constructed via the bootstrap.

Figure 3: Time Series Evolution of Average Alpha



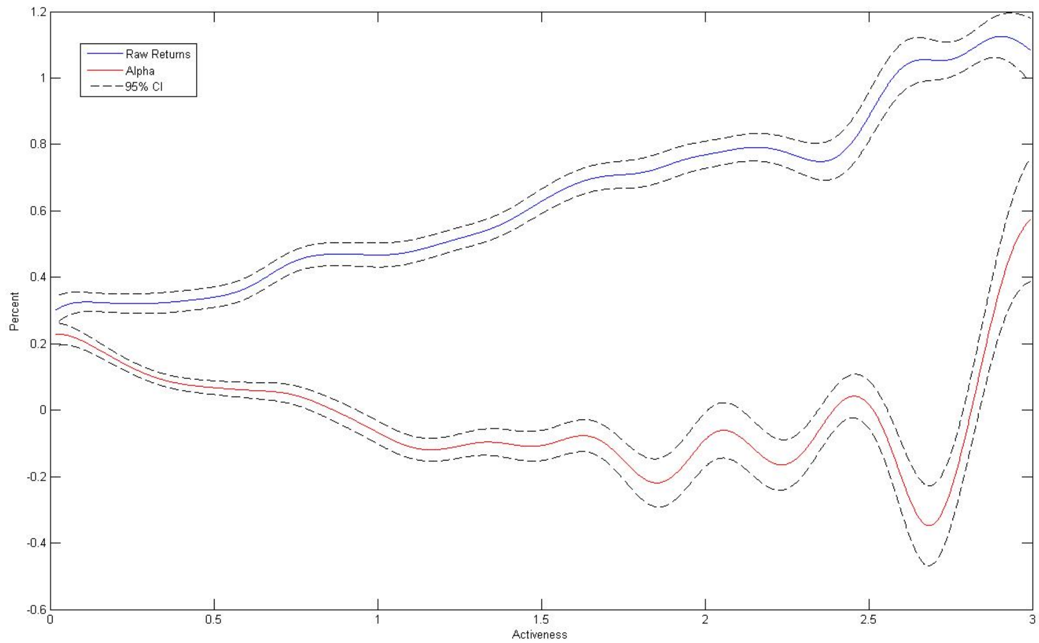
This figure plots the time-series evolution of average alpha for 3 different portfolios of managers: the top and bottom 5% of activeness and the interquartile range of activeness.

Figure 4: Distribution of Activeness



This figure displays the distribution of activeness relative to the average manager's activeness.

Figure 5: Kernel Regression Curves



This figure displays the curves implied by the two kernel regressions: one relating raw returns to activeness and one relating alpha to activeness. The non-parametric confidence bands are constructed by the method described in the footnote in the main text.