Board of Governors of the Federal Reserve System

International Finance Discussion Papers

Number 1112

August 2014

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August 8, 2014

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Returns to Active Management: The Case of Hedge Funds[1]

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Abstract

Do more active hedge fund managers generate higher returns than their less active peers? We attempt to answer this question. Using Kalman Filter techniques, we estimate the risk exposure dynamics of a large sample of live and dead equity long-short hedge funds. These estimates are then used to develop a measure of activeness for each hedge fund. Our results show that there exists a nonlinear relationship between activeness and performance. Using raw returns as a measure of performance, it is found that more active funds outperform the less active ones. However, when risk adjusted returns are used to measure performance, we find the opposite results; that is, activeness is inversely related to returns. Still, we find that a few very active managers outperform the moderately active funds and generate higher returns. We conclude that the most active managers use their skills to manage the riskiness of their portfolios and are, therefore, able to provide higher risk adjusted returns. Finally, we find that compared to the least active managers, the most active managers are less homogeneous and, therefore, due diligence is far more important when selecting an active manager.

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

JEL classifications: G11, G12, G14, G23

[1] 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.

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1 Introduction

Can managers' behavior predict returns in hedge funds? Since 1997, the hedge fund industry's assets under management (AUM) have increased by more than 14 times, with the AUM growing at an average pace of $100bn per year.[1] Hedge funds present themselves as absolute return investment vehicles, seeking to generate positive returns in any market condition. They can take short positions and are not subject to the strict mandates that govern mutual funds. Having such freedom in implementing investment strategies emphasizes the importance of the hedge fund manager's investment skills. Further, unlike the mutual fund industry, hedge funds charge both management and incentive fees, where the incentive fees provide option-like returns to managers.[2]. Given its loose investment mandate and fee structure, the hedge fund industry is expected to attract the most skilled asset managers.[3]

This paper investigates whether more active hedge fund managers perform better than those who are less active. Using a sample of 2,687 live and dead equity long-short hedge funds, the Kalman Filter is employed to estimate the risk exposure dynamics of each hedge fund, which then are used to create a measure of activeness for each fund.[4] This will allow us to study the relationship between activeness and performance.

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 security selection 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.

Our primary finding is that there exists a nonlinear relationship between activeness and performance, and that the relationship changes depending on whether raw returns or risk-adjusted returns are used to measure performance. In general, the moderately active funds tend to provide higher mean returns than the less active funds. But as the level of activeness increases, the mean returns tend to decline. When risk adjusted returns are used to measure performance, we find the opposite results. That is, the less active funds perform better than

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

[2] 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.

[3] 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/profile/john-paulson/

[4] We use the four factors of Fama, French and Carhart. They are based on the performances of the market portfolio, large vs small cap stocks, value vs growth stocks and stocks that display positive momentum vs those that display negative momentum.

the more active ones, but as the level of activeness increase, the risk-adjusted returns tend to increase. We may conclude that the highly active funds use their skills to manage the riskiness of their portfolios, improving the risk-return profiles of their funds. But it is less clear why, on a risk-adjusted basis, the less active funds can perform better than the moderately active funds when they underperform them in terms of raw returns. One can argue that the less active funds are long-term stock pickers, and, therefore, are able to generate better risk-adjusted performance without frequently changing their portfolios' risk exposures.

Using our measure of activeness, we create sub-samples of managers. Next, the risk-adjusted alphas of these sub-samples are estimated. Interestingly, we find that the average alphas for the more active sub-samples of managers are higher than those of the less active sub-samples. However, a higher percentage of less active managers have statistically positive alphas. This indicates that the highly active funds tend to be less homogenous than their less inactive peers. This would suggest that due diligence and manager selection is far more important when an investor is selecting from a group of active equity long-short managers.

Empirical studies of hedge funds performance can be broken into two broad groups. One set of papers examine the empirical properties of the time-series of hedge fund returns. This group of papers report mixed results regarding hedge fund managers' abilities in generating abnormal risk-adjusted returns.[5] In particular, recent studies tend to report very low or even negative risk-adjusted abnormal returns (i.e., alphas) 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 the strategy, delta of the incentive fee contract, level of co-investment by the manager and his/her level of education may affect a fund's performance.[7] This paper adds to these findings by reporting that cross-sectional differences in mean returns may be affected by the level of activeness of a fund.

The relationship between how activeness and performance has been addressed by two recent

[5]The anecdotal and academic evidence, at least for mutual funds, is fairly clear. For example, In 2011, 84% of actively managed U.S. equity mutual funds underperformed their benchmarks. For example, 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.

[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).

papers in the case of mutual funds. To obtain their results, these studies rely on reported security holdings. Huang, Sialm, 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 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 fund's holdings that do not overlap with that fund's stated benchmark portfolio. Their results indicate that more active funds tend to perform better. 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 use reported monthly returns as opposed to asset holdings to measure how actively each fund is managed.[8] It should be noted that the procedure developed in this paper can be applied to mutual funds as well.

This paper uses a return-based approach to estimate the exposure dynamics of our sample of hedge funds. Wermers (2011) warns of three potential problems when conducting returns-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. This paper focuses on hedge fund managers who invest in U.S. equity markets, and, therefore, we construct a model that reflects the equity risks they take (i.e., Fama-French-Carhart model). Second, by focusing on risk factors that have shown to affect 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, the results are corrected for potential heteroskedasticity when estimating the relationship between performance and our measure of activeness.

Carhart (1997) combines the three-factor model, developed by Fama and French (1992, 1993, 1996), and the momentum factor, developed by Jegadeesh and Titman (1993). Equation (1) represents the four-factor Fama-French-Carhart model:

$$r_{pt} - r_{ft} = \alpha_p + \beta_p(RMRF_t) + s_p(SMB_t) + b_p(HML_t) + m_p(UMD_t) + \varepsilon_{pt}, \quad t = 1, ..., T. \quad (1)$$

Here, r_{pt} is the rate of return on an asset, r_{ft} is the riskless rate, $RMRF_t$ is the excess return on the market portfolio and SMB_t, HML_t and UMD_t are returns to size, value and momentum factors, respectively. Factor exposures of the asset are measured by β_p, s_p, b_p, and m_p. Finally, the risk-adjusted performance of the investment is measured by α_p.

[8] Funds with more than \$100 million in assets have to report their long positions to the SEC. However, short positions are not reported.

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, this paper focuses on funds that follow equity long-short strategy in the U.S. markets. Consequently, we use the four-factor model of Fama-French-Carhart as its factors measure the systematic risks of the U.S. equity portfolios.

While Fung and Hsieh (2004) use look-back options to model trend-following strategies, Hasanhodzic and Lo (2007) employ multifactor models with time varying coefficients to accomplish the same goal. The authors use a rolling-window regression to capture the dynamics of hedge funds' investment strategies. As opposed to a constant-parameter regression, this methodology offers more insights into the empirical properties of hedge fund returns, but there is 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. This paper's objective is similar to that of Hasanhodzic and Lo (2007), as we also are interested in estimating the dynamics of hedge funds' exposures.

We employ the Kalman Filter approach with time-varying coefficients to model each hedge fund's return process. This allows us to obtain estimates of the time-series of each hedge fund's factor exposures, which are then used to create a measure of activeness for each fund. Mamaysky, et al (2004) show that a dynamic regression using the Kalman Filter performs better in explaining 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 of a multi-factor model using the Kalman Filter with that of a static linear model. 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. Even a linear static model with non-linear variables yields an adjusted R^2 of only 0.62. Roncalli and Teiletche (2007) compare estimates of dynamic risk exposures obtained using Kalman Filter to those obtained through a rolling window OLS approach. They find that the Kalman Filter produces smoother estimates of funds' factor sensitivities, and reacted to new information quicker than either the 12-month, the 24-month, or the 36-month rolling window techniques. Bollen and Whaley (2009) 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.

The rest of the paper is organized as follows. The next section explains the empirical strategy and explains the data used. Section 3 discusses results for different specifications and section 4 offers some concluding remarks.

2 The Model

We use a sample of U.S. long-short equity hedge funds. The goal is to estimate each hedge fund's exposures to risk factors and then create a benchmark for each manager.[9] Consider the general case of the excess return on a portfolio:

$$r_{p,t} - r_{f,t} = \sum_{i=1}^{n} \omega_{i,t-1}(r_{i,t} - r_{f,t}) \quad p = 1, ..., K \tag{2}$$

In equation (2) , $r_{p,t}$ is the hedge fund's returns at time t, $r_{f,t}$ is the risk-free rate at time t, $\omega_{i,t-1}$ is the weight on asset i decided at time period $t-1$, and $r_{i,t}$ is the time t return on asset i. The weight on risk-free rate in the portfolio is given by $(1 - \sum_{i=1}^{n} \omega_{i,t-1})$. The above expression is, in fact, an economic identity, as it describes how the excess return on a portfolio is simply 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, and thus the weights 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. Since hedge fund returns are generally available only on a monthly basis and most hedge funds have limited track records, the above regression cannot be estimated using a large set of asset returns as explanatory variables. Therefore, we employ the four-factor Fama-French-Carhart model as described in equation (1) to measure the risk exposures of each hedge fund. 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.[10] Thus, the econometric representation of the model is

$$r_{p,t} - r_{f,t} = \mathbf{w}'_{p,t-1}\mathbf{f}_t + \varepsilon_{p,t} \qquad p = 1, ..., K, \quad t = 1, ..., T. \tag{3}$$

Here, $\mathbf{w}_{p,t}$, is a 5×1 vector of weights (i.e., factor exposures and alpha), which will be estimated by the Kalman Filter. $\mathbf{f}_t$ is a 5×1 vector of Fama-French-Carhart factors and the constant term. The error term is represented by $\varepsilon_{p,t}$. Note that while equation (2) is an economic identity, and, therefore, does not contain an error term, equation (3) contains an error term as it approximates the portfolio's return process. The weights are assumed to follow the following autoregressive

[9] Since the Fama-French-Carhart 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.

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

process.

$$\mathbf{w}_{p,t} = \mathbf{w}_{p,t-1} + \boldsymbol{\mu}_{p,t}, \quad t = 1, ..., T,$$

where $\boldsymbol{\mu}_{p,t}$ is a vector of normally distributed random variables with mean zero.

Once the parameters of equation (3) are estimated, we can then measure the degree of activeness of each fund based on the variations in the estimated values of $\mathbf{w}_{p,t}$. The sum of absolute changes in $w_{ip,t-1}$, where i refers to ith factor, is used to measure the activeness of each portfolio. That is,

$$\phi_p = \frac{1}{T_p} \sum_{i=1}^{4} \sum_{t=2}^{T} |w_{ip,t} - w_{ip,t-1}|, \quad p = 1, .., K. \tag{4}$$

Here ϕ_p is defined as the measure of activeness of fund p.[11] Note that since our sample of hedge fund managers have track records of different lengths, the measure of activeness is adjusted by the length of the track record, T_p.

After the measure of activeness is obtained, we can examine the relationship between performance and the level of activeness. We use cross-sectional regressions to determine if there is a relationship between a hedge fund's performance and its degree of activeness. That is, we estimate the following regression

$$Z_p = \gamma_0 + \gamma_1 \phi_p + \tilde{u} \qquad p = 1, ..., K \tag{5}$$

Here, Z_p represents the performance of hedge fund p, ϕ_p measures how actively the fund is managed, and γ_i, for $i = 0, 1$ are the coefficients that have to be estimated. The hypothesis is that $\gamma_1 \leq 0$; i.e., a higher level of activity does not lead to better performance, and due to transaction costs, active funds tend to have lower performance compared to less active funds. This hypothesis basically claims that U.S. equity markets are efficient and that hedge funds managers are not skilled enough to overcome the transaction costs and the fees associated with managing a fund. Aknowledging the possibility of nonlinearities, we also include a square activeness term in the regression and show the results below.

One potential problem that arises in estimating the cross-sectional regression (5) must be noted. The explanatory variable ϕ_p is an estimate of the true measure of activeness, and, therefore, regression (5) suffers from errors in variables. This may lead to a downward bias in the estimated values of γ_1 and γ_2. We use Monte Carlo simulation 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

[11] The measure of activeness is similar to that of a portfolio's turnover. 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.

in the Appendix.

We use three different measures to represent the dependent variable Z_p. First, we employ the average excess return on each manager. This will determine if the more active funds can generate higher average net-of-fee returns. Of course, higher returns could be due to higher levels of risk assumed by the active managers. Consequently, two different measures of risk-adjusted excess returns, Sharpe ratio and Jensen's alpha, are used as well.

The data is obtained from the Center for International Securities and Derivatives at the University of Massachusetts-Amherst (CISDM). We consider 2,687 live and dead hedge funds whose Morningstar/CISDM category is listed as U.S. Long/Short Equity. These funds invest in U.S. stocks, 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. The sample covers 1994-2013. We winsorized the data at the 2% level and eliminated all funds that had less than 36 months of data, but no other restrictions on whether a fund is live or dead were imposed.[12] Duplicate funds were removed from the sample.

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

Tables 1 and 2 Here

Figure 1 Here

3 Results

3.1 Constant Coefficients

Before we apply the Kalman Filter, we estimate the following static OLS regression (6) using the entire sample.

$$r_{p,t} - r_{f,t} = \alpha_p + w_{1p}(RMRF_t) + w_{2p}(SMB_t) + w_{3p}(HML_t) + w_{4p}(UMD_t) + \varepsilon_{t,p} \qquad (6)$$

[12] The requirement that funds should have a minimum of 36 months of data may introduce survivorship and look ahead biases. Since we include dead funds in our sample, the impact of these biases on our results is mitigated.

This regression is the standard four-factor Fama-French-Carhart model, and was discussed in equation (1). We begin with the static model because it is the building block of the dynamic regression to follow. In addition, this allows us to compare our preliminary results with those reported in previous papers. We estimate regression (6) for each manager and report the average of the estimated coefficients. The results are presented in Table 3.

Table 3 Here

Note that most alphas are not significantly different from zero. In equation (6), the estimated mean abnormal return, α_p, was 0.223% per month. Of all 2,687 funds, 467 had significantly positive alphas at the 5% level. Since we are considering long-short equity funds, it is not surprising that we find a high percentage of funds have significant exposure to overall stock market risk ($RMRF$). In fact, this is the only risk factor that more than 50% of funds 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 (e.g., see Capocci (2013)).

3.2 Dynamic Coefficients

In this section, we estimate regression (6) for each manager assuming time-varying coefficients, using the Kalman Filter methodology.[13] Figure 2 displays the dynamics of the average estimated weights of the four factors. It can be seen that the weights are indeed time-varying, suggesting that fund managers actively adjust their exposures to various sources of equity risks through time.

Figure 2 Here

The estimated time-series of each manager's exposure to the four equity factors are, then, used to create a measure of activeness for each manager. As described in equation (4), a measure of activeness, ϕ_p, is constructed for each fund, which is then normalized to create a relative measure of activeness:

$$\rho_p = \frac{\phi_p}{\bar{\phi}} - 1,$$

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

where $\overline{\phi}$ is the mean of activeness measure for the entire sample. Therefore, ρ_p represents how active fund p is relative to the average fund. A value of 0 would indicate that a fund's level of activity is average, while a positive (negative) value means the manager is more (less) active than average. Observing this measure of activeness, we see that there are a handful of managers with extremely high levels of activeness (orders of three times the average activeness). Thus, we eliminate these outliers and consider only funds who have a value of ρ_p less than three. We do not find the same extreme outliers for negative values of ρ_p (i.e. less active funds). We are left with 2,674 managers.[14]

3.3 Sorting Results

Before estimating our cross-sectional regressions, some preliminary results are presented by sorting the entire sample into sub-samples consisting of the highly active and less active funds. We use the top (bottom) 5, 10 and 25 percent to create samples of the most (least) active funds. Table 4 presents the summary statistics for excess returns and activeness in each group. A t-test for the difference in means 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. Finally, while the most active funds tend to have higher skewness than the least active funds, all have roughly the same kurtosis. It important to note that the mean returns on the least active funds do not increase monotonically as activeness increases. This indicates that there may exist a non-linear relationship between performance and activeness.

Next, the same sub-samples of the most active and the least active funds are used to run the Fama-French-Carhart model with constant coefficients. The results, which are presented in Table 5, clearly suggest that the most active funds tend to have, on average, higher alphas than the least active funds. We see that compared to the least active funds, the most active funds tend to have higher exposures to the market and the size factors, and similar exposures to the value and the momentum factors. Finally, similar to the results reported in Table 4, we see that the relationship between alpha and activeness is not monotonic, reinforcing the idea that the relationship might be non-linear.

The higher exposure to the size factor is surprising because the bid-ask spread and price impact are larger for small cap stocks, which imposes higher costs on active managers. If, despite these added costs, these managers were able to produce higher returns than their less active peers, then the argument that active managers are more skilled than their less active peers would be strengthened.

[14] The results are similar for the whole sample.

Finally, results reported in Table 5 show that a much higher percentage of less active funds have statistically positive alphas. That is, while the average alphas of the active sub-samples are higher, fewer of those active managers have positive alphas. As mentioned, the most active managers have to overcome the higher levels of transactions costs, and, therefore, only those who are highly skilled can offer higher risk-adjusted returns; these results indicate that only a small group of equity long-short managers posses that level of skill.

Tables 4 and 5 Here

3.4 Regressions Using Raw Returns

Three cross-sectional regressions using our measure of activeness are estimated. First, we run regression equation (5) where the independent variable is the mean excess return of the fund. The regression employs White estimates of the variance covariance matrix of errors to correct for heteroskedasticity.[15] Also, throughout the paper, the estimated coefficients are corrected for errors in variables using the process described in the Appendix. Table 6 presents the results of this regression.

Table 6 Here

Table 6 presents two sets of results. Column (a) represents the cross-sectional results when activeness appears only in the linear form, while Column (b) includes the squared value of the activeness measure as well. We find that, γ_1, the coefficient on the measure of activeness is statistically significant and greater than zero at the 5% level. The result indicates that the more active funds tend to generate higher mean return. The results obtained from sorting our sample seemed to indicate that performance has a nonlinear relationship with activeness, and the figures appearing in Column (b) confirm this. We can see that γ_2 is negative and significant at 5% level. These findings indicate that the highly active or inactive funds tend to underperform the moderately active funds. The cut-off point, though, is close to a measure of activeness equal to 10, which is unrealistic for our sample. But, the relationship seems to support the idea that

[15] Given an $n \times n$ regressor matrix, $\mathbf{X}$, and OLS residual u_i for each observation, White's estimated variance-covariance matrix for $\hat{\boldsymbol{\beta}}$ is,

$$Var\left[\hat{\boldsymbol{\beta}}\right] = \left(\mathbf{X}'\mathbf{X}\right)^{-1} \mathbf{X}' diag\left(u_1^2 ... u_n^2\right) \mathbf{X} \left(\mathbf{X}'\mathbf{X}\right)^{-1}$$

See Greene (2011).

too much activeness will be associated with lower returns due to higher transaction costs. In the absence of significant differences in skills, we should expect to see lower average returns on the most actively managed portfolios. However, the cut-off seems to be above the range of available estimates of managers' behavior and transaction costs cannot explain why the least active funds tend to underperform the moderately active funds. This may lead us to conclude that moderately active fund managers are highly skilled compared to their less active peers. Of course, there is an alternative explanation: fund managers that are somewhat active tend to assume more risks, and this how they are able to generate higher returns.

3.5 Regressions Using Risk-Adjusted Returns

To explore the possibility that higher risk is responsible for higher mean returns offered by the moderately active funds, we re-estimate equation (5), using each fund's Sharpe ratio and Jensen's alpha as the dependent variables.[16] Jensen's alpha refers to the average value of the intercept in equation (1) with the factor exposures estimated using the Kalman Filter, and the Sharpe ratio, SR_p, refers to $(\bar{r}_p - r_f)/\sigma_p$, where $\bar{r}_p$ is the mean return on fund p, r_f is the riskless rate and σ_p is the standard deviation of return on fund p.

The results of estimating equation (5) when $Z_p = SR_p$ are presented in Table 7.

Table 7 Here

Again, similar to previous section we present both the estimation results for both the linear and non-linear equations. Column (a) of Table 7 shows that there exists a statistically significant negative relationship between activeness and the Sharpe ratio, although column (a) suggest that the estimate is very close to zero. Column (b) suggests that funds with an activeness level of above 2.4 generate higher returns that the less active ones. Previously, we reported higher mean return on the moderately active funds. Therefore, the above results indicate that returns to the moderately active funds are more volatile than those of the less active funds. Further, the increase in volatility is not commensurate with higher return leading to lower Sharpe ratios for the moderately active funds. The coefficient of the measure of activeness squared is positive and highly significant. This indicates that while the moderately active funds fail to generate higher Sharpe ratios compared to their less active peer, the highly active funds are able to increase their Sharpe ratios.

[16] For a discussion of the Sharpe ratio see Sharpe (1994).

This is surprising because we saw in the previous section that the mean returns on the highly active funds tend to be lower than those of the moderately active funds, while the results appearing in Table 7 indicate that the same managers are able to generate higher Sharpe ratios than moderately active funds. We may conclude that the highly active managers tend to be more skilled in managing the risk of their portfolios. The question that arises is whether these managers are skilled in managing both the total and the systematic risks of their portfolios.

Sharpe ratio adjusts returns for the total risk of a portfolio's return, while investors may demand compensation only for the systematic risk of the portfolio. To account for the systematic risk of each fund, we examine the relationship between its mean alpha and its level of activeness. We estimate equation (5) with the mean alpha of each fund as the independent variable, where mean alpha is estimated from the time-series of alphas generated by the dynamic four-factor model. The results are presented in Table 8. We report our findings for both linear and nonlinear cases.

Table 8 Here

Looking at Column (a), we see that the estimated value of γ_1 is negative and highly significant. Similar to the results obtained when Sharpe ratio was used to measure performance, this indicates that the moderately active funds tend to generate lower alphas than the less active funds. For the non-linear case, γ_1 is still negative and significant, while γ_2 is positive and highly significant. The cut-off is similar to the one in Table 7 and corresponds to a level of activeness of approximately 2.4. Again, similar to the previous results, we can see that the highly active funds are able to generate higher alphas than the moderately active funds.

Results of Tables 7 and 8 indicate that while, on a risk-adjusted basis, the less active funds tend to perform better than the moderately active funds, there are some highly active funds that could generate higher risk-adjusted returns. Further, we can conclude that most active fund managers do not have the skills to manage the risks generated by their trading strategies and that they tend to underperform their less active peers on a risk adjusted basis.

3.6 Live versus Dead Funds

Since our data consists of live and dead funds, we are, naturally, interested to see if the relationships between activeness and performance is the same for live and dead funds. One would expect that if our sample is restricted to include only "live" funds, a stronger positive relationship between activeness and performance will be observed. It may be that active managers who survive perform better than inactive managers that survive. We re-estimated the cross-section regressions of the last section for dead funds and live funds separately. For the purpose of this section, a fund is considered dead if it has no returns data in our database for the last 12 months. A fund is considered live if it has at least 60 months of data and has reported returns for the last 12 months. This leaves us with 1,588 dead funds and 789 live funds. We find almost identical results as in the full sample. The only differences are that we do not find a significant coefficient on activeness squared for live funds in the regression with alpha as a dependent variable. We also do not find evidence of non-linearities for dead funds when we consider the raw returns regression. We hypothesize that this is a time period specific phenomenon. We see that there is a sharp dropoff in the number of funds after the middle of 2007. Thus we divide our sample into the first 160 months and the last 80 months. We find a sharp contrast: The mean return for fund managers in the earlier sample is 0.9434%, while for the second sample it is -0.0396. Thus, the market environment was more favorable in the pre-2007 period. The results for live managers are the same as the full sample results when we restrict ourselves to the first time period. Similarly, non-linearities are found for dead funds when we consider the latter time period. Since, by definition, live funds have been functioning more recently than dead ones, we believe that these subsample regressions confirm our time dependence hypothesis. [17]

4 Conclusion

Do active hedge fund managers perform better than their less active peers? We use a sample of 2,687 U.S. equity long-short hedge funds covering 1994-2013, to answer this question. The Kalman Filtering approach is applied to this sample in order to estimate the dynamics of each fund's exposure to Fama-French-Carhart factors. The time-series of these exposures are then used to create a measure of activeness for each fund. Finally, using cross-sectional regressions we attempt to answer the question posed above.

The empirical evidence presented in this paper shows that there is a nonlinear relationship between performance and the measure of activeness. Interestingly, this relationship changes depending on whether raw returns or risk-adjusted returns are used to measure performance.

When raw returns are used as performance measure, we find that the moderately active funds tend to outperform the less active funds. However, as the level of activeness increases, the performance of the active funds declines. The returns in this industry seem to dwarf the higher transaction costs associated with actively managed portfolios for plausible levels of activeness

[17] We also estimated our cross-sectional regressions with AUM included as a control variable. Our sample was smaller in this case as we do not have AUM data for all the funds. However, there was no qualitative change in the results. All coefficients remained significant and their signs did not change.

and more active funds generate higher raw returns than their less active peers. Alternatively, we can interpret the results that the active funds have riskier investment strategies. To find out whether skill or risk is the reason for the higher return by the moderately active funds, we repeat the above analysis, but this time we use Sharpe ratios and Jensen's alpha as measures of performance. Our results show that the less active funds perform better than the moderately active funds on a risk adjusted basis. However, as the level of activeness increases, then at some point, the risk-adjusted returns of a few highly active funds begin to improve. The above results are robust and hold for both dead and live funds. In addition, when size is added as a control variable, the results remain virtually the same.

Another finding of this paper is that the least active funds tend to be more homogenous compared to their most active peers. While, on average, sub-samples of the active funds may have higher risk-adjusted returns than the sub-samples of the least active funds, lower percentage of the active managers have positive alphas. This indicates that only a small group of the most active managers posses the skills to overcome the higher transaction cost and provide positive risk-adjusted alphas. The implication for investors is that they need to spend more resources on due diligence and manager selection when considering active equity long-short managers.

5 Appendix

Consider equation (5) of the text

$$Z_p = \gamma_0 + \gamma_1 \phi_p + \tilde{\varepsilon} \qquad p = 1, ..., K$$

which will suffer from errors in variables as the measure of activeness has to be estimated. Here, we briefly describe our method for correcting out estimated coefficients for the presence of measurement error in independent variable. In general, it can be shown that[18],

$$plim \;\; \hat{\gamma}_1 \times \left(\left(\phi_p' \phi_p \right)^{-1} \left(\phi_p' \phi_p + u'u \right) \right) = \gamma_1$$

Here, $\hat{\gamma}$ is the biased estimate of the true γ when equation (5) is used. ϕ_p is a matrix of the true values of the independent variable, and u is a matrix of measurement errors that are independent of ϕ_p, the error term of the regression, and the dependent variable of the regression. Since we cannot observe the true value of ϕ_p, we estimate the adjustment matrix via simulation. We generate random exposures with means and volatilities that fall within the range of means and volatilities estimated for our sample. These random exposures are then used to generate the return on portfolio that invests the four factors. Using the same procedure that is employed to estimate hedge fund managers measure of activeness, the same measure is estimated for the simulated portfolio. Finally, the estimated value of the activeness measure is compared to its actual value. This procedure is repeated 1000 times, which allows us to obtain an estimate of

$$\left(\left(\phi_p' \phi_p \right)^{-1} \left(\phi_p' \phi_p + u'u \right) \right).$$

The value of this adjustment factor is used to remove the bias from the estimated value of γ_1.

[18] For a discussion of errors in variables see Greene (2011).

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Tables and Figures

Table 1: Average of Monthly Funds Excess Returns (%)			
	Mean	Max	Min
Average of Excess Returns	0.4804	111.8373	-100.2392
Standard Deviation	4.0665	20.8507	0.1661
Skewness	-0.3267	6.7555	-12.6061

Table 2: Average of Risk-Factors Monthly Returns (%)				
	RMRF	SMB	HML	UMD
Mean	0.6191	0.2144	0.2329	0.4636
Max	11.34	22.02	13.87	18.39
Min	-17.23	-16.39	-12.68	-34.72
Stand. Dev	4.5219	3.4438	3.2688	5.2885
Skewness	-0.7373	0.871	0.0298	-1.5916

Table 3: Static OLS of Equation (6)		
Regression is Run for Each Fund. Average Values of Results		
Variable	Mean Coeff. Value	% of t-stat sig. at 5%
Constant	0.223	17.38
RMRF	0.4788	82.51
SMB	0.031	21.14
HML	-0.0315	12.17
UMD	0.0483	29.21
% of F-Stat Sig. at 5%	88.537	
Mean R^2	0.3811	

Table 4: Summary Statistics for Sorted Sub-Samples			
	Top 25%	Top 10%	Top 5%
Mean	0.661	0.8034	0.8219
Mean Standard Dev.	6.2014	7.5604	8.6607
Mean Skewness	−0.2035	−0.0617	−0.0156
Mean Kurtosis	6.4423	6.8508	7.0568
Max Activeness	2.874	2.874	2.874
Min Activeness	0.2751	0.6456	1.0215
	Bottom 25%	Bottom 10%	Bottom 5%
Mean	0.3278	0.2841	0.3225
Mean Standard Dev.	2.1132	1.7306	1.5413
Mean Skewness	−0.5122	−0.6367	−0.616
Mean Kurtosis	6.888	7.5881	7.8586
Max Activeness	−0.3768	−0.5691	−0.6395
Min Activeness	−0.9824	−0.9824	−0.9824

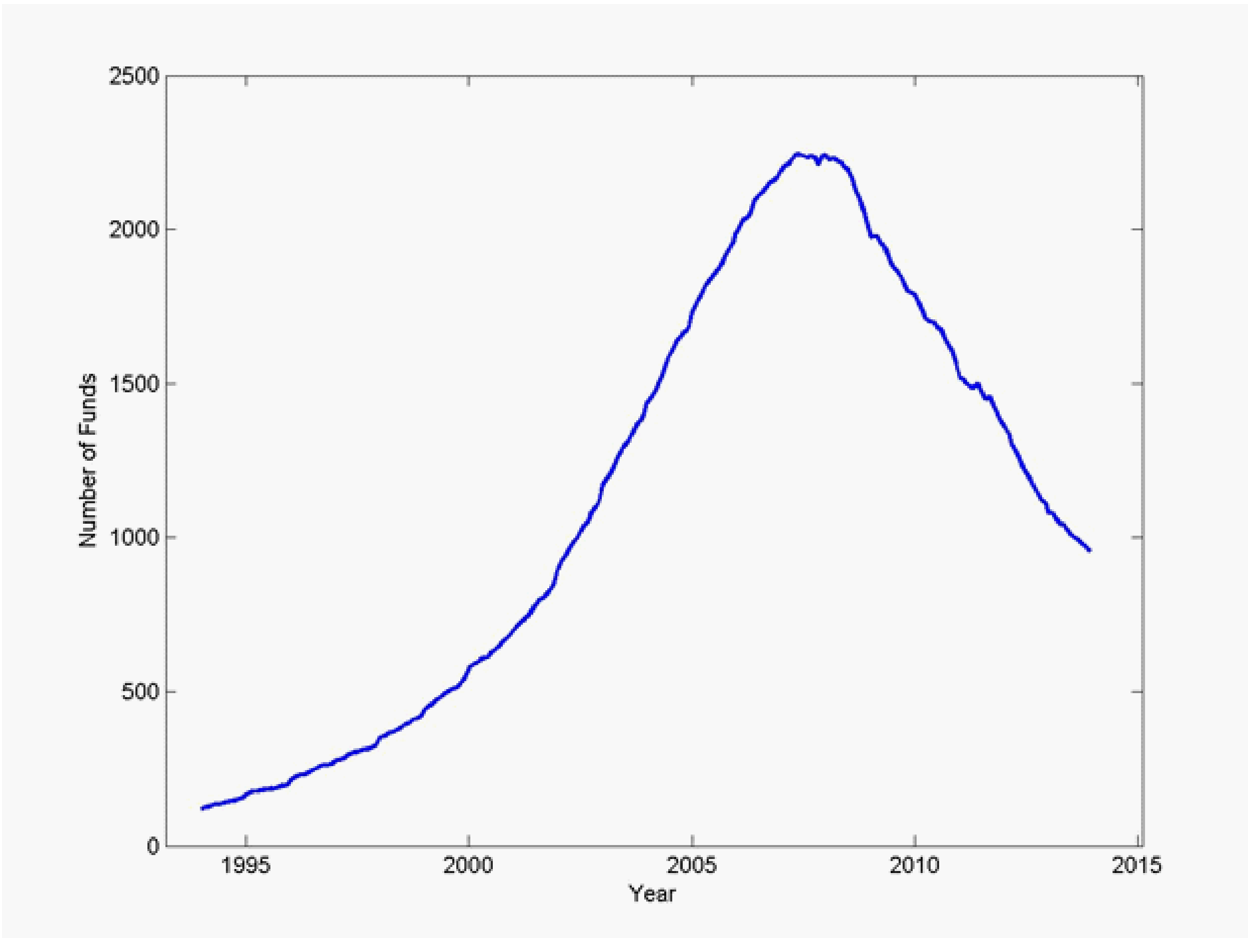
Tables 5: Regression (6) Applied to Sub-Samples						
	Top 25%		Top 10 %		Top 5%	
Variable	Mean Coeff.	% t-stat sig. at 5%	Mean Coeff.	% t-stat sig. at 5%	Mean Coeff.	% t-stat sig. at 5%
Alpha	0.3031	11.23	0.3899	9.36	0.3497	3.73
RMRF	0.69	81.44	0.7822	76.03	0.8929	73.88
SMB	0.0619	15.72	0.1579	16.1	0.1953	14.93
HML	−0.0376	10.33	−0.0468	7.12	−0.0676	6.72
UMD	0.049	20.96	0.0492	19.48	0.0503	20.9
Obs.	669		267		134	
Mean R^2	0.3456		0.3119		0.2915	
	Bottom 25 %		Bottom 10 %		Bottom 5%	
Variable	Mean Coeff.	% t-stat sig. at 5%	Mean Coeff.	% t-stat sig. at 5%	Mean Coeff.	% t-stat sig. at 5%
Alpha	0.1769	28.74	0.1508	32.21	0.1966	42.54
RMRF	0.2713	82.78	0.2292	83.52	0.2111	82.09
SMB	0.0518	27.69	0.0486	25.47	0.0455	25.37
HML	−0.0328	10.93	−0.0328	10.11	−0.0236	10.45
UMD	0.0516	45.81	0.0434	46.82	0.0305	41.04
Obs.	669		267		134	
Mean R^2	0.4152		0.4167		0.4003	

Table 6: Cross-Sectional Regression (5)		
Using Mean Excess Returns As Dependent Variable		
	(a)	(b)
Constant	0.4719	0.4782
t-values	(55.6402)	(46.3835)
Activeness	0.5225	0.6103
t-values	(25.3751)	(29.6144)
Activeness Sqr.		-0.0576
t-values		(-2.7237)
Obs.	2,674	2,674
R^2	0.0819	0.0826

Table 7: Cross-Sectional Regression (5)		
Using Sharpe Ratios As Dependent Variable		
	(a)	(b)
Constant	0.1378	0.1299
t-values	(47.4348)	(50.662)
Activeness	-0.0951	-0.1488
t-values	(-7.6055)	(-14.5264)
Activeness Sqr.		0.061
t-values		(9.153)
Obs.	2,674	2,674
R^2	0.0261	0.0376

Table 8: Cross-Sectional Regression (5)		
Using Alphas As Dependent Variable		
	(a)	(b)
Constant	0.0132	-0.0045
t-values	(1.1148)	(-0.2889)
Activeness	-0.2084	-0.3283
t-values	(-5.2837)	(-10.7154)
Activeness Sqr.		0.1365
t-values		(3.1132)
Obs.	2,674	2,674
R^2	0.0067	0.0097

Figure 1



2500
2000
1500
1000
500
0
Number of Funds
1995
2000
2005
2010
2015
Year

Figure 2