Asset Allocation Dynamics in the Hedge Fund Industry

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This Version: June 2011

Abstract

This paper examines asset allocation dynamics of hedge funds through conducting optimal changepoint test on an asset class factor model. Based on the average *F*-test and the Bayesian Information Criterion (BIC), we find that more dynamic hedge funds exhibit significantly better quality than less dynamic funds, signaled by lower return volatility, stricter share restrictions, and high water mark provision. In particular, a higher degree of dynamics is shown to be associated with better risk-adjusted performance at the individual fund level. We find that the degree of a fund's dynamics is closely related to share restrictions. However, the outperformance of highly dynamic funds is robust even after controlling for share restrictions. Sub-period analysis suggests that the superiority of asset allocation dynamics is mostly driven by performance during earlier time periods before the peak of the technology bubble. Fund flow analysis suggests that abnormal returns in the hedge fund industry are diminishing as capital flows in and arbitrage opportunities are not infinitely exploitable.

Key Words: Changepoint, Asset Allocation, Hedge Funds, Performance

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Compared to traditional investment vehicles such as mutual funds, hedge funds have greater flexibility in switching investment strategies, changing leverage, and making asset allocation decisions. As hedge funds are becoming more and more popular with institutional investors, assets under management have steadily grown from \$40 billion in 1990 to over \$2.2 trillion in 2008. Many hedge funds claim to offer absolute returns and they have been attracting increasing attentions from investors, regulators, and fund managers in the past decades. Using various hedging tools, hedge funds can reduce downside losses and preserve capital; for example, during 2008 when the average stock fund fell by about 40%, the average hedge fund dropped only about 20%, according to Morningstar[2].

After experiencing the 2007-2009 financial crisis and the more recent European sovereign debt crisis, retail investors are also seeking refuges despite the fact that hedge funds are open only to institutional investors and wealthy individuals. Hedged mutual funds, mutual funds mimicking hedge funds strategies, have recently emerged to fill this gap. According to Agarwal, Boyson, and Naik (2009), these hedged mutual funds still underperform hedge funds in general. They propose a regulation and incentive hypothesis to explain this underperformance. Compared to those hedged mutual funds, hedge funds enjoy unique regulatory advantage[3] and charge performance fee imbedded in the fee contract. Given the large size of the hedge fund industry with about 9,000 hedge funds, we believe that many hedge funds have been unable to exploit the regulatory advantage and capture alphas in both up and down markets. We intend to explore this cross-

[2]The numbers are cited from the *Wall Street Journal*, May 1, 2010, "Safe Haven: Mutual Funds That Act Like Hedge Funds".

[3] Hedge funds are largely free from charter restriction and have much more freedom to move across diverse asset classes as compared to mutual funds.

sectional variation within our hedge fund sample in this paper and explore which hedge funds are more dynamic in making asset allocation decisions. This is an important question as dynamic hedge funds may switch among various asset classes and deliver superior returns than non-dynamic hedge funds. The existing hedge fund literature has documented such cross-sectional variation from various aspects, e.g. Sun, Wang and Zheng (2009) propose a measure of strategy distinctiveness and find that this measure is positively associated with hedge fund performance. In this paper, we focus on the funds that have dynamic features by holding diverse asset classes and moving across them. In other words, we explore whether dynamic hedge funds with frequent adjustment in asset allocation can outperform non-dynamic funds that make stale assets allocations. Asset allocation is generally defined as the allocation of an investor's portfolio among a number of major asset classes.

The literature on hedge fund dynamics is growing. For example, Fung and Hsieh (1997) find that hedge fund strategies are highly dynamic, different from the buy-and-hold strategy held by mutual funds. Agarwal and Naik (2004) use option-based returns to capture the nonlinear behavior in hedge fund returns. Chen and Liang (2007) illustrate that the market exposure of self-claimed market-timing hedge funds varies with changes in market return and volatility. Bollen and Whaley (2009) show that a sizable portion of hedge funds shift their risk exposures significantly over time. They also acknowledge that any accurate appraisal of hedge fund performance must recognize such freedom and the implied dynamics. Patton and Ramadorai (2009) propose a new method to capture hedge fund dynamics by using high frequency instruments. Our paper relates to the literature on hedge fund dynamics and investigates whether hedge funds allocate assets dynamically among five asset classes, e.g. equity, bond, commodity, currency and credit.

Sharpe (1992) initiates the style analysis of mutual funds; such methodology is also adopted in hedge fund studies (see Brown, Goetzman, and Park (2000), Brown and Goetzman (2003)). As suggested in Sharpe (1992), a simple regression approach typically provides more than enough information for the purpose of asset allocation[4]. With an optimal changepoint regression model similar to that in Bollen and Whaley (2009), we are able to categorize hedge funds into dynamic funds and non-dynamic funds. This categorization is implemented by following the idea of average *F*-tests in Andrews and Ploberger (1994). We study the characteristics of dynamic funds by means of both fitting a logistic regression model and conducting two-sample *t*-test. We find that dynamic hedge funds have had significantly better quality, signaled by stricter share restrictions to investors, high water mark provision in charging incentive fee and lower volatility in returns; dynamic funds also demonstrate a greater level of the first-order autocorrelation in returns, suggesting more illiquid holdings.

One problem of fitting the optimal changepoint regression model is to determine the number of changepoints. While the timing of change is usually determined by minimizing the residual sum of squares when the number of changepoints is preset, there is no efficient way to estimate the appropriate number of changepoints. Previous literature implements the optimal changepoint regression model by assuming a single changepoint and determines the timing of change by trying all permissible change dates

[4] While it is more accurate and exact to attempt to determine a fund's exposures from a detailed analysis of the securities held by the fund, the lack of hedge fund holding information makes it unrealistic.

and retaining the one that generates the minimum residual sum of squares.[5] We relax this assumption by allowing multiple changepoints to accommodate the dynamic feature of hedge fund strategies. The timing of change is still estimated by minimizing residual sum of squares. Then we determine the number of changepoints by minimizing the Bayesian Information Criterion (BIC). While increasing the number of changepoints usually decreases the minimum residual sum of squares, it is not necessarily associated with a smaller BIC since under the BIC adding more parameters result in a penalty. In fact, we find that allowing up to two changepoints is optimal for over 95% of the hedge funds in our sample.

As determined by the BIC, each hedge fund can have zero, one, or two changepoints. We make the estimated number of changepoints represent the degree of dynamics-hedge funds with no changepoint are considered as least dynamic while hedge funds with two changepoints are categorized as most dynamic and one changepoint reflects moderately dynamic. As suggested by Bollen and Whaley (2009), we realize this structural change and analyze the performance of each fund by segment breaking at the estimated change dates. The time series of average alpha demonstrates that the most dynamic funds outperform the moderately dynamic funds, which in turn outperform the least dynamic funds. The performance difference is very dramatic in the early years of our sample; however the performance difference gradually fades away over time, especially after the technology bubble, possibly due to industry competition and diseconomy of scale.

We further examine such a performance difference on both the net returns and the risk-adjusted returns. With the net returns in consideration, we allow a five-number

[5] See Bollen and Whaley (2009).

summary proxy for the empirical distribution and investigate the cross-sectional distribution of the Sharpe ratio, maximum drawdown and the number of negative months at each dynamic level. With the risk-adjusted returns, we follow Kosowski, Timmermann, Wermers, and White (2006) and draw inference on the cross-sectional distribution of the *t*-statistics of alpha by bootstrapping the *p*-values. The comparison suggests that more dynamic funds provide better risk-adjusted return than the less dynamic funds and this outperformance is robust even after controlling for share restrictions. Consistent with the results of our time series analysis, the outperformance of hedge fund portfolios with more dynamics is driven by earlier time periods; when we look at the post-technology bubble sub-period, the hedge fund portfolios exhibit no alpha at any dynamic level.

We interpret our empirical findings as follows: in the earlier periods, more skillful hedge fund managers are able to make better use of the regulatory advantage, trade more dynamically with diverse asset classes and move frequently across them at the proper time, and deliver superior risk-adjusted returns. These funds impose stricter withdraw restrictions on investors, which give managers less funding fluctuations and thereby provide the funds with more flexibility in taking advantage of various arbitrage opportunities across assets and allow managers hold more illiquid positions. With this industry attracting more investor capital and facing stronger competition, hedge funds are gradually losing the superiority in trading due to limits to arbitrage opportunities. This interpretation is further supported by analysis on fund flows. This finding is also consistent with Goetzmann, Ingersoll, and Ross (2003) that arbitrage returns may be limited, leading to diseconomy of scale. Some other papers also examine the capacity constraints on hedge fund strategies, e.g. Naik, Ramadorai, and Stromqvist (2007) and

Ammann and Moerth (2005). They provide evidence on a concave relationship between the level of returns and assets under management, consistent with Getmansky (2004) that an optimal size for hedge funds exists. Our results are also consistent with Fung, Hsieh, Naik, and Ramadorai (2008) that diminishing returns to scale combined with the inflow of new capital into better performing funds leads to the erosion of superior performance over time.

One contribution of this paper is to relax the assumption of a single changepoint when examining hedge fund asset allocation dynamics by conducting the optimal changepoint regression on hedge fund returns. This is an important extension designed to reflect the dynamic nature of hedge fund trading strategies. To our best knowledge, this is the first paper that studies the characteristics and performance of hedge funds distinguished by asset allocation dynamics. Our empirical finding is consistent with the hedge fund literature that capacity constraint exists in hedge fund strategies and capital inflows erode the continuing profitability of the industry.

The rest of the paper is organized as follows. Section I describes the methodology, especially on how we implement the optimal changepoint regression model. Section II describes the data. Section III provides empirical results and Section IV presents robustness check and extended analysis. Finally, Section V concludes.

I. Methodology

The optimal changepoint regression framework models hedge fund dynamics assuming that a fund's exposures to the underlying risk factors undergo discrete shift over time where the timing of each shift is to be determined from the data. While unknown, the number of discrete shifts is usually preset at one. In section I.B, we explain how to relax the assumption of a single structural change and allow up to two changepoints.

We consider the situation of "pure structural change" where exposures to different risk factors change at the same time in contrast to "partial structural change" when only one factor changes at each time. Since we aim to model hedge funds' asset allocation dynamics and use five different asset class factors, it makes more sense to follow pure structural change rather than partial structural change. We make such a choice by considering that hedge fund managers shift asset allocations with limited capital, which implies capital transferred from one asset class to another. This assumption reflects the supplementary effects of investors' wealth invested among various assets. Partial structural change models assume exposure to one asset class increase/decrease while exposures to the other asset classes are unaffected. Thus partial structural change assumes that capital is created to increase the single risk exposure, or hedge fund managers decrease the single risk exposure and hold more cash.

Mathematically, this optimal changepoint regression model is simply the standard linear regression model as in equation (1) with X being the designed matrix. The entire statistical hypothesis will be the shift on the factor exposure vector β_t with the first element being α:

$$y_t = X_t^T \beta_t + \delta_t \qquad (1)$$

A. Optimal Change Point Test

With the model specified in equation (1), the null hypothesis is the case when no structural change occurs[6], which transfers to the following:

$$H_{0:}\ \beta_t = \beta$$

Econometrics literature has documented several alternatives for testing structural change in linear regression models. They are the generalized fluctuation test framework by Kuan and Hornik (1995) and the *F*-test framework by Andrews (1993), Andrews and Ploberger (1994). Some of these econometric methods have already been applied in hedge fund studies. For example, Fung and Hsieh (2004) apply the CUSUM test, which belongs to the generalized fluctuation test framework on returns of fund of hedge fund index and demonstrate time varying exposures to the Fung and Hsieh (2004) seven-factor model from capturing fluctuations in the residuals.

The *F*-test framework is a rather different approach since the alternative is specified. Whereas the generalized fluctuation tests are suitable for various patterns of structural changes, the *F*-test is designed to test against a single shift alternative. Thus, the alternative can be formulated on the basis of the model specified in equation (1) as:

$$H_{\alpha:}\ \beta_t = \beta_A \quad if\ 1 \le t \le t_0,$$

$$\beta_t = \beta_B\ \ if\ \ t_0 < t \le T.$$

With the date of changepoint t_0 unknown, the idea is to calculate the *F*-statistics for all potential changepoints or for all potential changepoints within an interval and to reject the null hypothesis if any of those statistics becomes too large. Intuitively, the series of *F*-statistics can be aggregated into one test statistic in more than one way. Andrews (1993) and Andrews and Ploberger (1994) suggest three different test statistics respectively: *Sup_F*, *Ave_F*, and *Exp_F*. The *Sup_F* statistic and the *Ave_F* statistic

[6] Asset class exposure changes can be due to leverage effect, we control for leverage in later analysis.

rejects the null hypothesis respectively when the maximal or the mean *F*-statistic gets too large; both tests have certain optimality properties, according to Andrews and Ploberger (1994).

In section III, we report our empirical results from conducting the *Ave_F* test with *p*-values approximated based on Hansen (1997). This is similar to the test applied in Bollen and Whaley (2009) when they use bootstrapped critical values and rigorously test the power of the model.

B. **Number of Change Points**

While the *F*-test framework mentioned in section I.A is constructed to test for the alternative hypothesis of a single shift, we propose that a hedge fund manager may significantly shift asset allocations more than once during the sample period of January 1994 to December 2009. It is a challenge to determine efficiently the optimal number of changepoints; we follow a statistically intuitive way to relax the assumption of the single changepoint.

When the number of changepoints is preset, the date of changes can always be estimated by minimizing the residual sum of squares from trying all permissible change dates. When one changepoint is allowed, the number of permissible change dates is about the same as the total number of observations T; for the case of two changepoints, the number of permissible change date pairs is about (T-1)(T-2); and etc. Thus, with the number of changepoints increasing, the number of permissible change dates increase much faster and estimating the optimal change dates is computationally expensive when we have a great number of permissible change dates.

With more changepoints allowed, the minimum residual sum of squares can always be decreased. We apply the Bayesian Information Criterion (BIC) to panelize for more changepoints and determine the optimal number of changepoints by minimizing the BIC, which considers both the goodness of fit and the number of parameters[7]. In fact, we tried allowing up to five changepoints and found that almost no fund in our sample yields an optimal number of changepoints of more than three while the number of funds with exactly three changepoints is small and negligible. As a result, we report the empirical results in section III up to two changepoints only.

II. Data

We obtain hedge fund data from Lipper/TASS, one of the main hedge fund databases used by academics. To limit survivorship bias, we include both live and defunct funds. Our sample period spans from January 1994 to December 2009, which covers two major abnormal events, the technology bubble in 2000 and the subprime crisis in 2008. We follow the hedge fund literature and filter out noise funds using the following criteria: most recent assets under management of $10 million or more, reporting monthly net-of-fee returns, assets denominated by the US dollar only. We are also concerned about the possibility and influence of backfilling bias[8]. We retrieve the

[7] An alternative approach is to conduct a series of sequential *F* tests, testing the significance of change from 0 to 1 change point, then from 1 to 2 change points if the previous test results in a rejection, and so on. This sequential testing statistical approach is in spirit similar to the one used in Rio and Garcia (2010) to determine the number of options needed. A concern with this approach is that the result should be very sensitive to the choice of significance level, e.g. whether to conduct test on testing more change point depend on the rejection decision with the previous test.

[8] At reporting to a database, managers can voluntarily provide the data vendor with their track records, where there is no guarantee that the reported historical performance has been audited and validated. Moreover, funds with better track records have better incentive to provide the historical return voluntarily.

date on which a specific fund is added to the TASS database and deem the period between the date of the first reported return and the adding date as the incubation period. If the adding date is missing for a fund, we use the first 12 months to proxy for the incubation period. To correct for the backfilling bias, data from the incubation period are dropped for each fund.

After the above data filtering and cleaning, we require each fund to have at least a four-year return history, or 48 monthly observations to be included in the sample in contrast to the standard two- to- three-year requirement. This is mainly driven by our desire to have enough observations for more reliable changepoint estimates and for performance evaluation breaking at the estimated dates. Moreover, in Section III, we test and show that the number of observations of dynamic funds is not statistically different from that of non-dynamic funds. So, this filtering rule should have no significant effect on our empirical results on comparison. On the other hand, we should not require an unreasonably large number of observations if we want to have a sizeable sample of hedge funds included in our study. Four years seems as a reasonable compromise considering both aspects[9].

Based on the above filtering criteria, our sample ends up with 1,283 hedge funds[10] including 728 live funds and 555 defunct funds across 12 self-claimed styles, including Long/Short Equity Hedge, Equity Market Neutral, Dedicated Short Bias, Fixed Income Arbitrage, Convertible Arbitrage, Emerging Markets, Global Macro, Managed Futures, Multi-Strategy, Event Driven, Option Strategy, and Fund of Funds. Funds with missing

[9]For robustness, we run all the empirical tests with hedge fund data when each fund is required to have five years' data, 60 monthly observations. Although not included here, all the major conclusions hold. Moreover, empirical results in Section III suggest that fund classification is insensitive to number of observations.
[10] A 24-month, 36-month, or 60-month requirement will instead give a sample size of 2,277, 1,686 or 964 funds, respectively.

self-reported style are counted as the "Other" category. Panel A of Table I contains detailed summary statistics for the sample. Over the period of 1994-2009, returns across different styles exhibit great heterogeneity: Emerging Market funds produce the highest excess return of 0.94% while Dedicated Short Bias funds give only 0.07% on a monthly basis. Both Fixed Income Arbitrage and Convertible Arbitrage funds have high kurtosis, indicating fat tails due to the speculative behaviors of these funds.

As previously stated, our main goal is to model hedge funds' asset allocation dynamics. Thus, excess returns of different asset classes will be our risk factors in use when we apply the factor model. We select risk factors covering five major asset classes, e.g. equity, bond, commodity, currency, and credit. Specifically, the factors are the S&P500 Total Return, the Barclays Aggregate Bond Index, the S&P GSCI Total Return, the Federal Reserve Board (FRB) broad dollar index, and the monthly change in the Moody's Baa yield less 10-year treasury constant maturity yield. Summary statistics of these five factors, including the correlation matrix, are included in Panel B of Table I.

To understand the explanatory power of these five selected factors on our sample of hedge funds with a simple regression, we first conduct an OLS regression on each equally-weighted style portfolio with these five factors. An adjusted R-square of 55.14% is produced for the all-fund portfolio. In Table II we report details regarding the results of the OLS regressions for each hedge fund style portfolio. Each of the five risk factors proves to be statistically significant for a wide range of styles. Comprehensive styles like Fund of Funds and Multi-Strategy have greater adjusted R-squares and significant exposures for more asset classes while the multi-variate regression model proves to be less powerful for less comprehensive but more focused styles such as Managed Futures and Options Strategy. On average, most styles demonstrate positive alpha with the OLS regression, with significance in styles such as Equity Market Neutral, Multi-Strategy, Global Macro and Event Driven. It is well known in the mutual fund literature that asset allocation accounts for a large part of the variability in mutual fund returns. For hedge funds, the power of an asset class factor model is significantly lower due to other unknown risk exposures and potential dynamics in asset allocations.

We need fund flow data in the analysis conducted in Section IV. To compute the dollar flows for each fund in each month, we use monthly assets under management (AUM)[11] as well as the monthly return data and follow the computation used in Naik, Ramadorai, and Stromqvist (2007).

$$F_{it} = A_{it} - A_{it-1}(1 + r_{it}) \qquad (2)$$

Once the net flows for each fund *i* in each month *t* are computed, we compute flows at each dynamic level by aggregating individual fund flows up to the level of dynamics:

$$f_{dt} = \sum_{i=1}^{N_d} F_{it} \qquad (3)$$

To compare the net flows across different dynamic levels, we also compute a flow

[11] The AUM (asset under management) data may be missing for some funds for some months. To handle such missing data problem, for each fund each month we set the monthly flow at zero if the AUM data is missing or if the AUM of previous month is missing.

ratio which scales the dollar flows by the aggregated end-of-month AUM from the previous month at each dynamic level:

$$R_{dt} = \sum_{i=1}^{N_d} F_{it} \, / \sum_{i=1}^{N_d} A_{it-1} \qquad (4)$$

III. Empirical Results

A. Optimal Change Point Regression

As explained in section I, we conduct two statistical procedures with the optimal changepoint regression model on each hedge fund. The first one is to implement an *Ave_ F* test against the null hypothesis of no structural change. The other procedure is to estimate the optimal number of changepoints by means of minimizing the BIC. The results regarding these two procedures are grouped by style and included in Panel A and Panel B of Table III, respectively.

In Panel A, we count the number/percentage of funds by two different levels of *p*-values from conducting the *Ave_F* test. *p*-values greater than 0.05 correspond to the case of insignificant test statistic and non-dynamic funds; *p*-values less than or equal to 0.05 refer to the case of significant test statistic and dynamic funds. Out of all funds, 61% yield significant test statistics and suggest those funds with dynamic asset allocations. This result is consistent with Bollen and Whaley (2009) that a large proportion of hedge funds undergo significant structural shift in terms of risk exposures while they use strategy factors instead of asset class factors[12]. Distributions of the *p*-value breakdown

[12] Here, we apply an asset class factor model in particular to capture asset allocation dynamics. While it is more exact to determine a fund's asset class exposure from a detailed analysis of the holdings, it is not an

differ by style considering that some styles are more likely to swift allocations across different assets, e.g. convertible arbitrage, fixed income arbitrage and fund of hedge funds.

As reported in Panel B of Table III, we estimate the optimal number of changepoints by minimizing the BIC when up to two changepoints are allowed. While the dates of changes can be estimated by minimizing the residual sum of squares when the number of changes is preset, no efficient way exists for estimating the number of changepoints. This is a separate statistics procedure from the *Ave_F* test since the *Ave_F* test is designed with an alternative hypothesis of a single changepoint. Thus, results in the two panels of Table III are not necessarily comparable. e.g., a hedge fund that has a significant test statistic *Ave_F* in Panel A may suggest zero changepoint from minimizing the BIC in Panel B.

As previously explained, we tried allowing up to five changes points and found that allowing no more than two changepoints is sufficient. As shown in Panel B of Table III, 59% of the funds have zero changepoints as suggested by the BIC while only 29% of the funds have one changepoint and only 12% of the funds are estimated as having two changepoints. In contrast, we classify 39% funds as non-dynamic funds and 61% as dynamic funds according to the *Avg_F* test.

As presented in Table II, the explanatory power of our asset class factor model varies across style categories; the adjusted R square is as high as 60% for the Long/Short Equity Hedge portfolio while it is as low as 2% for the Equity Market Neutral portfolio. To make sure that our fund classification from conducting the optimal Changepoint

option for hedge funds considering the data availability. According to Sharpe (1992), a simple approach of multiple regression analysis provides enough information for purpose of asset allocation.

regression model is not driven by the cross-sectional difference in model's power, we compare the adjusted R square for funds at different dynamic levels. Results are included in Panel C of Table III. As shown in Panel C of Table III, hedge funds at higher dynamic level do not necessarily produce a higher average adjusted R square[13]. As a matter of fact, distribution in the adjusted R square is fairly close across the three dynamic levels.

B. Fund Characteristics: Dynamic Funds vs. Non-Dynamic Funds

Again, we utilize the result in Panel A of Table III to classify each hedge fund as either a dynamic fund or non-dynamic fund. A hedge fund is considered to be dynamic if the associated *Ave_F* test statistic is statistically significant at the 5% level;[14] otherwise, the fund is classified as non-dynamic in terms of making asset allocation decisions.

To examine how the characteristics of dynamic funds differ from those of the non-dynamic funds, we implement the standard two-sample *t*-test[15] and report the results in Panel A of Table IV. The empirical results suggest that dynamic funds generally impose stricter share restrictions, e.g. longer lockup periods and longer redemption notice periods. This is consistent with the expectation that stricter share restrictions imply lower capital fluctuations and more flexibility for managers, which enable skillful hedge fund managers to have more freedom in shifting assets among various asset classes. We also notice that dynamic funds have significantly higher first-order autocorrelations[16], which

[13] We find that the results from conducting the *Ave_F* test are mildly related to the power of the model. Funds with *p*_value greater than 5% have the adjusted R-square averaging at 22.12% while the number is 24.90% for funds with *p*_value equal to or less than 5%.

[14] Later, we will avoid using this 5% as a significance level cutoff to classify dynamic funds and non-dynamic funds, but to study the continuous *Ave_F* value directly. As presented in Panel C of Table IV, we have consistent finding.

[15] Nonparametric test, if conducted here, will give exactly the same significance level.

[16] This significant autocorrelation can be due to the presence of either stale or "managed" prices. We apply the technique in Asness, Krail, and Liew (2001) and re-compute autocorrelation by using aggregated

suggests more illiquid holdings or return smoothing as suggested by Getmansky *et al*. (2004). Thus, dynamic funds are found to offer both less funding liquidity and less asset liquidity. In addition, dynamic funds have significantly less volatility in returns, which is consistent with the high first-order autocorrelation, or to the argument for return smoothing. We also look at the number of observations/fund age and find no difference between dynamic funds and non-dynamic funds. This suggests that the results from conducting the *Ave_F* test should not be induced by the difference in the number of observations.

To examine additional categorical characteristics that are associated with asset allocation dynamics, we fit a logistic regression model and present the results in Panel B of Table IV. We consider only dummy variables with the logistic model, e.g. style dummy, effective audit dummy, high water mark dummy[17], onshore dummy, live dummy, personal capital dummy and leverage dummy[18]. Empirical results suggest that Convertible Arbitrage, Fixed Income Arbitrage, and Funds of Funds are more likely to be classified as dynamic funds while Managed Futures[19] or equity styles such as Long/Short Equity Hedge and Dedicated Short Bias are less likely to be dynamic in making asset

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quarterly data. Although to a smaller magnitude, we still find dynamic funds having significant greater autocorrelation.

[17] We acknowledge the possible problem in hedge fund database that these dummy variables, e.g. audit dummy or high water mark dummy can be mis-recorded due to operational mistake or set as default by mistake.

[18] As shown, a leverage dummy proves to be insignificant when added into the logistic regression model. Thus, we have more confidence to believe structural change to asset factors is due to asset allocation adjustment rather than change of leverage.

[19] While Managed Futures is always considered as a dynamic style, it is shown here to be relative static in terms of asset allocation. There are several possible explanations. One is that while Managed Futures fund is likely to be exposed to multiple asset classes (we find that 60% Managed Futures funds trade index futures, 69% trade fixed income futures, 83% trade commodity futures and 66% trade currency futures), the allocation may be relatively static across asset classes even though it may follow dynamic trading within a certain asset class. A second is to assume that optimal change point regression model is not able to capture high frequency dynamics by allowing only a few change points, this explanation is less likely to be true in light of the evidence in Bollon and Whaley (2009).

allocation decisions. This is intuitive: broader styles such as fund of funds has a need for allocating assets among different asset classes while more focused styles invest in relatively narrow classes only. Moreover, funds with high water mark provisions are more likely to be classified as dynamic. Together with longer notice and lockup period, high water mark provisions indicate a high quality manager, consistent with the fact that skillful managers make better asset allocation decisions.

To avoid defining dynamic funds in a discrete way by a significance level cutoff, we examine the continuous *Ave_F* statistics directly and regress the *Ave_F* statistics on fund characteristics. Results are included in Panel C of Table IV. The results in Panel C are consistent with those in Panel A in terms of redemption notice period, volatility and autocorrelation except that lockup period loses its significance[20]. In addition, fee characteristics are added to the model. Incentive fee proves to be positively correlated with the *Ave_F* statistics, meaning that only high quality managers can charge high incentive fees while low quality managers cannot afford to mimic.

Overall, dynamic funds are found to have better quality as signaled by different fund characteristics, e.g. stricter share restrictions on investors, high water mark provision, greater incentive fee, and less volatility in returns.

C. Dynamics and Performance

In this section, we utilize the result in Panel B of Table III from minimizing the BIC and assign each hedge fund a dynamic level corresponding to the estimated optimal number of changepoints. As a result, a fund with two changepoints is considered as most

[20] As in the logistic model, leverage variables, e.g. maximum leverage and average leverage have no effect in determining the scale of the test statistics.

dynamic while a fund with zero changepoints is classified as least dynamic, and one changepoint goes with moderately dynamic.

Next, we examine the relation between dynamic level and fund performance. We use the intercept/alpha to represent the risk-adjusted performance and examine performance differences on both the net return and the risk-adjusted performance. Our hypothesis is that the most dynamic funds outperform the least dynamic ones.

With the net return, we examine several statistics including Sharpe ratios, maximum drawdowns, and number of negative months. Results are included in Panel A of Table V. The means of performance measures seem to suggest that for funds with a higher dynamic level, we tend to have greater Sharpe ratios, smaller maximum drawdowns and a lower number of negative months. Besides the evidence in the mean performance measures, the most-dynamic funds tend to have greater Sharpe ratios, smaller maximum drawdowns and a lower number of negative months in most quintiles than moderately or least dynamic funds. This pattern is less consistent comparing least and moderately dynamic funds except that moderately dynamic funds have a lower number of negative months in all quintiles. Even though different performance measures evaluate performance from a different angle, all seem to agree with the expectation that the most-dynamic funds outperform the least-dynamic funds. After all, these measures of net return do not adjust for risk except for the Sharpe ratio.

With risk-adjusted performance, we draw inference on the cross-sectional distribution of *t*-statistics of the alpha. We follow exactly the methodology introduced by Kosowski, Timmermann, Wermers and White (2006) and report the results in Panel B of

Table V[21]. Kosowski *et al*. (2006) use a bootstrap approach to test if the estimated alpha is due to random chance. The basic idea is to bootstrap under the null hypothesis of zero alpha, then compare the observed cross-sectional distribution of alpha *t*-statistics with that generated by the simulation. Out of our 500 simulations[22], the bootstrap *p*-value corresponds to the percentage number of simulations that have quintile alpha *t*-statistics greater/less than the observed one if it is positive/negative. Thus, this methodology is able to test manager skills controlling for sample variability or luck.

In Panel B, we observe the uniformly monotonic pattern, e.g. a greater dynamic level has greater alpha *t*-statistics in all of the right tails, starting from the 75% percentile. With regard to the left tails of 25% or less, the monotonic pattern is kept in the minimum *t*-statistics. For the other left tail percentiles, we do not see such a clear pattern and the corresponding bootstrapped *p*-values are insignificant in many cases. This cross-sectional distribution of *t*-statistics reveal that except for the minimum, the poor performance from the rest of the left tail cannot be totally attributed to poor manager skill, but rather, to sample variation or luck as shown by the relatively large *p*-values. At the same time, the good performance in the right tails is significantly different from zero as reflected by the *p*-value of zero, too good to be explained by randomness. From Panel B of Table V, we can conclude that in most percentiles of the *t*-statistics, especially in the right-hand-side percentiles/better performing funds, funds at higher dynamic levels outperform those at the lower dynamic level. This kind of fund level analysis is very powerful in detecting

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[21] Results included in Table V are based on a factor model of five asset class factors, which are described in Section II. Although not included in the paper, when we apply an alternative factor model of Fung and Hsieh seven factors as in Fung and Hsieh (2004), we are able to get the same pattern in the cross-sectional distribution of alpha t statistic cross dynamic levels.

[22] 500 are large enough for computing stable bootstrapped *p*-value; we test and find that 1,000 or 2,000 simulations will give exactly the same significance.

manager skills and is also applied in other hedge fund studies, e.g. Kosowski, Naik, and Teo (2007), and Cao, Chen, Liang, and Lo (2009).

To summarize, we find that funds being dynamic in making asset allocation decisions offer better risk-adjusted returns; the more dynamic funds in general have better quality, which is signaled by stricter share restrictions on investors, high water mark provision, higher incentive fees, and less volatility in returns. This is consistent with a separate equilibrium: high quality managers are able to signal themselves using stricter share restrictions and deliver better performance through dynamic asset allocation while low quality managers cannot afford to mimic.

IV. Robustness Check

We conduct several robustness checks in this section, including ruling out the alternative explanation of lockup premium and conducting accurate performance appraisal through segment linear regression breaking at the estimated change dates. In addition, we conduct sub-period performance analysis and fund flow analysis to better address the implication of diseconomy of scale of hedge fund strategies. Moreover, we explore more details in the discovered hedge funds' structural shifts, including the timing of the shifts and the directions of the shifts.

A. Lockup Premium

We discovered in previous sections that dynamic hedge funds are associated with stricter share restrictions and also the degree of dynamics is positively related to the risk-adjusted performance. Hence, the outperformance of dynamic funds could be due to the lockup premium as examined in Aragon (2007). To rule out the possibility of lockup premium, we redo the performance comparison by controlling for share restrictions.

Effective share restriction, defined by combining the redemption notice period and lockup period, is classified into three groups. The first group contains funds with effective share restriction of 1 month or less, the last group consists of funds with effective share restrictions of 13 months or longer, and the middle group has the rest. A two-way table of dynamic level and share restriction level is presented in Panel A of Table VI. Each share restriction group has 51% to 69% least dynamic funds, 20% to 36% moderately dynamic funds and 11% to 13% most dynamic funds. Thus, the distribution of dynamic level fund is not clustered in any specific share restriction group. Although the least dynamic funds are more numerous in the least share restriction group, which agrees with the results is Table IV, we still have a reasonable distribution spread out on share restriction level and dynamic level.

In Panel B of Table VI, we present fund level risk-adjusted performance with a breakdown in three different share restriction groups. Results in Panel B of Table VI come from the same methodology applied in Panel B of Table V, but controlling for share restrictions. What we can observe is that the monotonic pattern in performance from the least dynamic funds to the most dynamic funds is never reversed in any share restriction group, although the overall pattern is best reserved for the significant right tail quintile of 75% or higher (good performers) and is strongest in the greatest share restriction group. Consistent with the results in Panel B of Table V, we reject the hypothesis that performance of the good performers is due to luck but we fail to reject the null hypothesis that the bad performers in the left-tail funds are due to random chance.

In Panel C of Table VI, we regress the alpha *t*-statistics on our estimated optimal number of change points, controlling for a series of relevant fund characteristics. Results in Panel C suggest that controlling for share restrictions, fees, and leverage, the estimated optimal number of change points is positively and significantly correlated with the alpha *t*-statistic. Regression results in Panel C further confirm our hypothesis that dynamic funds outperform non-dynamic funds.

B. Accurate Performance Appraisal

As suggested by Bollen and Whaley (2009), accurate performance appraisal must recognize the discrete structural changes that hedge funds undergo; evaluate performance by conducting a static linear regression is not always reliable. With such a consideration, we re-evaluate each hedge fund by performing segment linear regression breaking at the estimated change dates.

To present fund performance at each dynamic level, we take the cross-sectional average alpha from those funds at each time under the same dynamic level and plot the time series of alpha in Figure I. Consistent with our previous findings, the figure clearly shows that the most dynamic-funds (with two changepoints) outperform the moderately dynamic funds (with one changepoint), which in turn outperform the least dynamic funds (with zero changepoint).

We can also notice from Figure I that the performance difference is mostly driven by earlier time periods before 2000; after that there is no performance difference with alphas from all three dynamic groups converging to zero.

C. Diseconomy of Scale

To verify further the issue of diminishing return to scale, we implement a portfolio level performance analysis over three sub-periods, e.g. with breakpoints corresponding to the collapse of Long-Term Capital Management in September 1998, and the peak of the technology bubble in March 2000[23]. These results are included in Table VII. Table VII are portfolio level results while Table V and Table VI are fund level results. Consistent with Figure I, dynamic funds are able to offer significantly positive alpha in earlier time periods while in the post-technology bubble sub-period, none of the fund portfolios is able to offer positive alpha at any dynamic level. The during-technology bubble sub-period is very special with portfolios at all dynamic levels showing strong alpha and displaying stronger significant and negative exposures to the credit factor, which implies the credit widening event caused by equity market crash impacts hedge funds adversely. The strong alpha during the technology bubble sub-period is also consistent with the finding in Fung, Hiseh, Naik and Ramadorai (2008). In their sample period of 1995 to 2004, the average fund of funds has only delivered alpha from October 1998 to March 2000 out of all three distinct sub-periods.

While we find from the time series analysis that the advantage of possessing dynamic features in making asset allocation decisions is fading away, we are interested to know whether this finding is due to diminishing returns to scale and the inflow of new capital into better skilled funds as suggested in Fung, Hsieh, Naik, and Ramadorai (2008).

To address this hypothesis, we examine the time series property of flows to funds at different dynamic levels. To quantify the monthly net fund flow to each hedge fund,

[23] The sub-period breakdown follows that employed in Fung, Hsieh, Naik, and Ramadorai (2008). It is also applied in Naik, Ramadorai, and Stromqvist (2007).

we use monthly net return and monthly AUM data as in equation (2). Then we aggregate the fund flows across funds at different dynamic levels and compute total net flow and net flow ratio[24] for each year from 1995 to 2009 as in equations (3) and (4). Results are included in Table VIII Panel A. As expected, in the pre-technology bubble years when more dynamic funds outperform, e.g. 1995, 1996 and 1997, investors' capital flowed from less skilled/least dynamic funds to more skilled/ moderately and most dynamics funds; in the during-technology bubble years when funds at all dynamic levels are capable of generating alpha, e.g. 1998, 1999 and 2000, capital flow among the three groups of funds with no clear trend with moderately dynamic funds mostly attracting investor flows; in the early years of post-technology bubble period when hedge funds' alphas are trending downward, e.g. 2001-2007, hedge funds are attracting huge investment capital as a whole reflected in capital inflow in all three dynamic groups; in the most recent two crisis years, e.g. 2008 and 2009, investors become less tolerant of risk and escape from the hedge fund universe, reflected in capital outflows in all three dynamic groups.

In Table Panel B of VIII, we investigate the question of whether investor flows help forecast return. A popular way to address this question was proposed by Granger (1969) and popularized by Sims (1972). Particularly, we follow a simple approach by using the autoregressive specification of a bivariate vector autoregression assuming an autoregressive lag of length 3.

$$R_t = intercept + a_1 R_{t-1} + a_2 R_{t-2} + a_3 R_{t-3} + b_1 F_{t-1} + b_2 F_{t-2} + b_3 F_{t-3}, \qquad H_0: b_1=b_2=b_3=0$$

[24] As in Naik, Ramadorai, and Stromqvist (2007), net flow ratio is the total annual net flow over the total AUM at the year-end of the previous year.

Testing causality, in the Granger sense, involves using *F*-tests to test whether lagged flow provides any statistically significant information about return in the presence of lagged return. If not, then flow does not Granger-cause return. Considering that with lagged returns, the test is valid only asymptotically; we derive the test results from the asymptotically equivalent Chi-square test. According to the *p*-values in Panel B of Table VIII, the test results are significant for about 25% funds at each dynamic level in each sub-period considered. The average coefficients on lagged flows are mostly negative; the significance is stronger in the more dynamic hedge fund group. Previous literature mostly tests whether hedge fund performance predicts flows, e.g. Fung, Hsieh, Naik and Ramadorai (2008); our interest here is instead to investigate whether investor flows predict performance for some funds during certain time periods.

D. Timing and Direction of the Shifts

By minimizing the Bayesian Information Criterion (BIC) to take into account both goodness of fit and the number of parameters, we have categorized our hedge fund sample with respect to the optimal number of shifts. To better assess the nature of the shifts that are identified from the return data, we take a closer look at the timing of the shifts and the direction of the shifts.

Our sample extends from January 1994 to December 2009; each hedge fund possesses a unique sample period within that time span. Based on our categorization, we have moderate dynamic funds each with one shifting point and most dynamic funds each with two shifting points. The dates of the shifts are identified by minimizing the sum square of residuals; the result is summarized in Figure 2. In Figure 2, we plot histogram on the shifting year for both moderate dynamic funds and most dynamic funds. While we observe that a large portion of the shifts take place in the year of 2007, we add to the plot the shifting month distribution of those 2007-shiftings.

As we observe in Figure 2 that a large number of the shifts take place during the crisis, we expect to see a decrease in performance measure in the post-shift sub period compared to the pre-shift sub period. To verify such an expectation, we present in Figure 3 the box plot of alpha *t*_statistic for the pre-shift and post-shift sub periods[25]. Considering each shift an event, the dates of the event differs by funds. Suggested by Figure 3, the empirical distribution of alpha *t*_statistic of the moderate dynamic funds moves clearly to the negative direction after the event except for a few outliers with large positive alpha *t*_statistic. However, for the most dynamic funds with two shift points, we observe the change in the shape, rather than magnitude, of the empirical distribution.

V. Conclusion

In this paper, we examine hedge fund manager skills through asset allocation dynamics by examining the number of changepoint in asset class factor model. We interpret that exposure changes in asset class factors are related to skills in transferring assets from one market to another after controlling other factors such as leverage and share restrictions.

We contribute to the hedge fund literature in three aspects. First, we relax the

[25] In results that are not included in the draft, we find that a majority of factor betas move to the positive direction after the shift. The exact change in beta around shift-event differs by hedge fund style category and risk factor (equity, bond, commodity, currency, or credit). For space concern, we exclude box plots of beta *t*_statistic around shift-event.

assumption of a single changepoint in Bollen and Whaley (2009) when conducting the optimal changepoint regression model on hedge fund returns. With this assumption relaxed, we are able to capture hedge fund trading behavior more realistically and examine fund performance at different levels of dynamics. Second, to the best of our knowledge, this is the first paper to study fund characteristics and the performance of dynamic funds relative to non-dynamic funds in terms of asset allocation dynamics. We find that asset allocation dynamics are associated with share restrictions; funds having stricter share restrictions tend to be more dynamic. Also, a positive relationship is found between the degree of dynamics and the risk-adjusted performance. The more dynamic a fund is, the better the performance tends to be. The performance difference between the most and least dynamic funds is robust after controlling for share restrictions and performance appraisal by segments in linear regression settings. Finally, the time series analysis suggests that, in the past decade, hedge funds have been losing the advantage of possessing dynamic features and moving across diverse assets to capture absolute alpha. This finding is consistent with the fact that arbitrage opportunities are not infinitely exploitable and returns in the hedge fund industry are diminishing in scale as pointed by Berk and Green (2004). This interpretation is further supported by the time series property of fund flows that we document.

Based on our empirical findings we interpret that in earlier periods before the technology bubble there exists hedge funds that are more skillful in making use of regulatory advantage and moving across diverse asset classes than other hedge funds. These funds with more dynamics in general impose stricter share restrictions; hold more illiquid positions and offer better risk-adjusted returns. However, with the industry getting more competitive and more capital flowing in, hedge funds have gradually lost the ability to offer positive alpha through asset allocation dynamics. Our evidence is consistent with Fung, Hsieh, Naik, and Ramadorai (2008) that diminishing returns to scale combined with the inflow of new capital into better performing funds leads to the erosion of superior performance over time.

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Table I. Summary Statistics

Panel A reports summary statistics across the sample of 1,283 hedge funds over the period of January 1994 to December 2009. Data is provided by Lipper/TASS, regular criterion is followed to filter out noise funds, including most recent assets under management of $10 million or more, monthly net of fee returns are provided, and assets are denominated by the US dollar only. Return data is corrected for backfilling bias. In addition, we look at only long-history funds by requiring a minimum of four-year data (48 monthly observations). This results in 1,283 hedge funds including both live funds and defunct funds. The summary statistics include the number of funds (live and defunct) and the cross-sectional averages of the mean monthly return in excess of risk free rate, Mean; of the standard deviation of monthly excess returns, Std; of the Sharpe ratio, SR; of the skewness, Skew; and of the excess kurtosis, Kurt. Panel B reports summary statistics of factors over the period of January 1994 to December 2009. We select basic asset class factors that cover equity, bond, commodity, currency, and credit markets. Specifically, the five factors are the excess return of the S&P500 Total Return; of the Barclays Aggregate Bond index, Bond; of the S&P GSCI Total Return, Commodity; of the FRB broad dollar index, Currency; and the monthly change in the Moody's Baa yield less 10-year treasury constant maturity yield, Credit.*, **, and *** indicate a significance level of 10%, 5%, and 1% respectively.

Panel A. Summary Statistics of Hedge Funds

Category	# Live	# Defunct	Mean (%)	Std (%)	SR	Skew	Kurt
Long Short Equity Hedge	199	167	0.55	4.25	0.15	-0.14	2.86
Equity Market Neutral	21	33	0.29	1.91	0.18	-0.07	2.94
Dedicated Short Bias	4	7	0.07	5.64	0.03	0.54	1.04
Fixed Income Arbitrage	17	29	0.29	2.55	0.55	-1.71	15.48
Convertible Arbitrage	12	28	0.28	2.99	0.22	-0.94	9.96
Emerging Market	64	30	0.94	5.83	0.17	-0.82	6.11
Global Macro	32	20	0.73	3.86	0.18	0.26	2.32
Managed Futures	63	13	0.80	5.43	0.15	0.16	1.95
Multi-Strategy	37	19	0.42	3.12	0.18	-0.78	4.90
Event Driven	69	50	0.42	2.49	0.23	-0.81	5.86
Option Strategy	5	0	0.35	2.86	0.17	0.94	9.60
Fund of Funds	187	145	0.26	2.55	0.13	-1.10	5.13
Other	18	14	0.56	3.19	0.20	-0.93	8.15
All	728	555	0.47	3.55	0.17	-0.58	4.80

Panel B. Summary Statistics of Factors

	Equity	Bond	Commodity	Currency	Credit
Mean (%)	0.42	0.21	0.33	-0.24	2.31
Std (%)	4.47	1.11	6.53	1.42	0.90

Correlation Matrix of Factors

	Equity	Bond	Commodity	Currency	Credit
Equity	1	0.09	0.17**	-0.40***	-0.17**
Bond		1	0.05	-0.19***	0.15**
Commodity			1	-0.36***	-0.16**
Currency				1	0.06
Credit					1

Table II. Estimates of the OLS Linear Regression

This table reports the results of OLS linear regression on each equally weighted style portfolio, the construction of which includes both live funds and defunct funds. The five factors are the excess return of the S&P500 Total Return, Equity; of the Barclays Aggregate Bond index, Bond; of the S&P GSCI Total Return, Commodity; of the FRB broad dollar index, Currency; and the monthly change in the Moody's Baa yield less 10-year treasury constant maturity yield, Credit. Estimates and adjusted *R*-Square, Adjusted R^2 across each style category are reported. *, **, and *** indicate a significance level of 10%, 5%, and 1% respectively.

Style	Num. Funds	Intercept (%)	Equity	Bond	Commodity	Currency	Credit	Adj.R^2(%)
Long Short Equity Hedge	366	0.58	0.42 ***	-0.14	0.07 ***	-0.16	0.02	61.64
Equity Market Neutral	54	0.46 **	-0.00	-0.06	-0.00	-0.12 *	-0.10	1.58
Dedicated Short Bias	11	1.17	-0.89 ***	0.65 **	-0.00	0.05	-0.42	51.01
Fixed Income Arbitrage	46	0.50	0.07 **	0.39 ***	0.07 ***	0.15	-0.12	15.27
Convertible Arbitrage	40	-0.00	0.25 ***	0.11	0.06 ***	-0.17	0.22	34.54
Emerging Markets	94	-0.01	0.53 ***	-0.53 **	0.13 ***	-0.60 ***	0.44	42.56
Global Macro	52	1.94 **	0.30 ***	1.08 ***	0.11 **	0.90 ***	-0.39	18.19
Event Driven	119	0.58 **	0.20 ***	-0.04	0.05 ***	-0.03	-0.07	44.36
Managed Futures	76	0.80	-0.15	0.92 **	0.14 **	-0.01	-0.06	4.42
Multi-Strategy	56	1.07 ***	0.12 ***	0.03	0.06 ***	-0.20 **	-0.24 **	36.16
Option Strategy	5	-0.00	-0.03	-0.13	-0.01	-0.19 **	0.21 *	1.38
Fund of Funds	332	0.36	0.21 ***	0.01	0.09 ***	-0.04	-0.07	43.22
Other	32	-0.01	0.16 ***	0.22 **	0.07 ***	-0.21 **	0.17	43.75
All	1,283	0.40	0.25 ***	-0.01	0.08 ***	-0.10	0.02	55.14

Table III. Optimal Change Point Test and Optimal Number of Change Points by BIC

We test for each individual hedge fund against the null hypothesis of no structural change. Follow Andrews (1993), and Andrews and Ploberger (1994), we aggregate a series of *F*-statistics into a single mean test statistic, *Ave-F*, which has certain optimality properties. Panel A reports the results of the *Ave-F* tests, including the number/percent of funds of each style with significance/insignificant test statistics. The *p*-values are approximated based on Hansen (1997). Then for each fund, we allow for up to two change points and estimate the timing of changes by minimizing the residual sum of squares. Finally, we decide on the optimal number of change points by minimizing the Bayesian Information Criterion (BIC). Panel B reports the resulted distribution of number of change points for each style category. In Panel C, we summarize the power of the asset class factor model (adjusted R square) for funds of different dynamic categories, which are categorized in Panel B.

	Panel A. Optimal Change Point Test: Ave-F Test				Panel B. Number of Change Points by BIC					
Strategy	*p*-value>0.05		*p*-value<=0.05		0		1		2	
	Number	Percent	Number	Percent	Number	Percent	Number	Percent	Number	Percent
Long Short Equity Hedge	179	0.49	187	0.51	254	0.69	81	0.22	31	0.08
Equity Market Neutral	26	0.48	28	0.52	34	0.63	14	0.26	6	0.11
Dedicated Short Bias	8	0.73	3	0.27	8	0.73	1	0.09	2	0.18
Convertible Arbitrage	9	0.23	31	0.78	16	0.40	16	0.40	8	0.20
Fixed Income Arbitrage	11	0.24	35	0.76	17	0.37	18	0.39	11	0.24
Emerging Markets	40	0.43	54	0.57	54	0.57	28	0.30	12	0.13
Global Macro	25	0.48	27	0.52	43	0.83	8	0.15	1	0.02
Event Driven	39	0.33	80	0.67	51	0.43	56	0.47	12	0.10
Managed Futures	47	0.62	29	0.38	66	0.87	8	0.11	2	0.03
Multi-Strategy	19	0.34	37	0.66	28	0.50	13	0.23	15	0.27
Option Strategy	1	0.20	4	0.80	4	0.80	1	0.20	0	0.00
Fund of Funds	93	0.28	239	0.72	169	0.51	116	0.35	47	0.14
Other	9	0.28	23	0.72	13	0.41	14	0.44	5	0.16
All	506	0.39	777	0.61	757	0.59	374	0.29	152	0.12

Panel C. Adjusted R Square by the Number of Change Points					
# Change Points	# Funds	Mean (%)	Standard Deviation (%)	Minimum (%)	Maximum (%)
0	757	22.48	18.87	-7.04	84.76
1	374	26.52	19.37	-5.65	90.65
2	152	23.66	16.53	-5.38	83.12

Table IV. Fund Characteristics and Dynamics

This table examines the connection between dynamics and fund characteristics. In Panel A and Panel B, we define a dynamic fund as having *Ave_F* statistic significant at 5%. In Panel C, we avoid using a significance level cutoff and study the continuous *Ave_F* statistics directly. Characteristics considered include lockup period, redemption notice period, fund age (number of observations), volatility, and the first-order autocorrelation. Panel A reports the mean and *t* statistic on testing the difference. Panel B gives the results of fitting a logistic model with 1 being assigned to dynamic funds. We consider dummy variables for the logistic model, including style dummies, audit/ high water mark/ leverage/ personal capital/ onshore/ live dummies. Panel C reports a regression of *Ave_F* statistics on fund characteristics, fee characteristics are added. *, **, and *** indicate a significance level of 10%, 5%, and 1% respectively.

Panel A. Mean Characteristics of Dynamic Funds and Non-dynamic Funds

	Dynamic Funds	Non-dynamic Funds	Difference_*t*
Number of Funds	777	506	
Lockup (months)	4.57	3.33	2.80 ***
Notice (days)	43.89	34.82	5.94 ***
Fund Age (months)	83.89	83.78	0.06
Volatility	0.03	0.04	-6.63 ***
1^{st} Order Autocorrelation	0.25	0.14	10.02 ***

Panel B. Logistic Model with Probability Modeled for Dynamic Funds

Dummy Variable	Model 1	Model 2	Model 3
Intercept	0.31***	0.40***	0.20
Convertible Arbitrage		0.84**	0.83**
Dedicated Short Bias		-1.38**	-1.43**
Emerging Markets		-0.10	0.02
Equity Market Neutral		-0.32	-0.39
Event Driven		0.32	0.35
Fixed Income Arbitrage		0.73**	0.67*
Fund of Funds		0.54***	0.67***
Global Macro		-0.32	-0.37
Long Short Equity		-0.35**	-0.38**
Managed Futures		-0.88***	-0.82***
Multi-Strategy		0.27	0.24
Option Strategy		0.99	1.10
Other		0.75*	0.69
Audit	0.03		0.08
High Water Mark	0.22***		0.27***
Leverage	0.02		0.07
Personal Capital	-0.16***		-0.15**
Onshore	0.00		0.08
Live	-0.06		-0.05
Pseudo *R*-square (%)	2.27	7.57	10.23

Table IV. (Cont.)

Panel C. Regression of the *Ave_F* Statistic on Fund Characteristics		
	Coefficient	*t*-statistic
Intercept	9.09	6.29***
Redemption Notice Period	0.05	3.68***
Lockup Period	0.01	0.13
Incentive Fee	0.09	1.86*
Management Fee	-0.27	-0.48
Volatility	-40.15	-2.91***
1^{st} Order Autocorrelation	17.51	9.38***
Average Leverage	0.00	0.19
Maximum Leverage	0.00	1.58
Adj_R^2 (%)	13.19	

Table V. Performance and the Degree of Dynamics

Each fund is assigned a dynamic index with three levels, 0 or 1 or 2, which corresponds to the number of change points estimated by minimizing BIC. Thus, funds with dynamic index of 0 are least dynamic while dynamic index of 2 denotes most dynamic funds. Risk-adjusted performance is evaluated by fitting linear factor model using five risk factors covering equity, bond, commodity, currency and credit markets. Panel A gives a five number summary for each performance measure for funds at each dynamic level. Performance measures include Sharpe ratio, maximum drawdown and number of negative months. Panel B gives cross-sectional distribution on fund-level *t*-statistics of alpha following Kosowski *et al*. (2006); 500 simulations are conducted for each fund; bootstrapped *p*-values of *t*-statistics are shown in the parenthesis underneath.

Panel A. Performance Comparison on Net Returns						
	min	25%	50%	mean	75%	max
Sharpe Ratio						
Least Dynamic	-0.36	0.10	0.17	0.19	0.25	1.38
Moderately Dynamic	-0.28	0.09	0.16	0.19	0.26	1.00
Most Dynamic	-0.19	0.07	0.15	0.28	0.27	5.20
Maximum Drawdown						
Least Dynamic	0.01	0.13	0.21	0.26	0.33	1.36
Moderately Dynamic	0.01	0.11	0.17	0.22	0.28	1.77
Most Dynamic	0.00	0.11	0.17	0.22	0.27	0.79
Number of Negative Months						
Least Dynamic	0	26	39	42	56	95
Moderately Dynamic	0	21	27	30	38	81
Most Dynamic	0	19	28	29	38	80

Panel B. Cross-Sectional Distribution of alpha *t*-statistics within Each Dynamic Group										
	Min	1%	5%	10%	25%	75%	90%	95%	99%	Max
Least Dynamic	-4.31	-2.63	-1.49	-0.97	-0.23	1.40	2.24	2.78	3.89	6.73
	(0.02)	(0.04)	(0.99)	(1.00)	(1.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Moderately	-3.67	-2.73	-1.54	-1.10	-0.11	1.97	3.09	3.84	5.81	7.87
Dynamic	(0.09)	(0.15)	(0.86)	(0.98)	(1.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Most Dynamic	-2.60	-2.57	-1.57	-0.93	-0.20	2.03	3.42	4.82	9.21	13.20
	(0.52)	(0.22)	(0.64)	(0.99)	(1.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

Panel VI. Share Restrictions and the Degree of Dynamics

We discover that funds with dynamics impose significantly more share restrictions and funds with greater dynamic level offer significantly higher alpha. This table examines in more detail the relationship between share restriction and dynamic. Redemption notice period and lockup period are summed to denote overall effective share restriction, SR (in months); overall effective share restriction is categorized into three levels. Panel A gives a two-way table reporting number of funds for each dynamic index level and for each share restriction level. Panel B draws inference on the cross-sectional distribution of fund-level alpha *t*-statistics within each share restriction category for each dynamic group. Following Kosowski *et al*. (2006), bootstrapped p-values are simulated with 500 simulations and included in the parenthesis underneath. In Panel C, *t*-statistic of alpha is regressed on estimated number of change points (Num. Change Points) controlling for a series of relevant fund characteristics, including management fee (mfee), incentive fee (ifee), lockup period (lockup), redemption notice period (notice), average leverage (avglev). *, **, and *** indicate a significance level of 10%, 5%, and 1% respectively.

Panel A. Two-Way Distribution Table of Effective Share Restriction and Dynamic Level

	All	Least Dynamic		Moderately Dynamic		Most Dynamic	
		Number	Percent	Number	Percent	Number	Percent
SR<=1	548	378	0.69	109	0.20	61	0.11
1<SR<13	405	205	0.51	147	0.36	53	0.13
SR>=13	330	174	0.53	118	0.36	38	0.12
All	1283	757	0.59	374	0.29	152	0.12

Panel B. Cross-Sectional Distribution of alpha *t*-statistics for Each Dynamic Group by Share Restriction

	Min	1%	5%	10%	25%	75%	90%	95%	99%	Max
Effective Share Restriction<=1 month										
Least Dynamic	-4.31	-2.43	-1.51	-0.97	-0.32	1.29	2.07	2.67	3.89	6.73
	(0.01)	(0.44)	(0.92)	(1.00)	(1.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Moderately Dynamic	-3.29	-2.73	-2.02	-1.30	-0.69	1.71	2.66	3.35	3.65	3.71
	(0.09)	(0.08)	(0.03)	(0.50)	(0.42)	(0.00)	(0.00)	(0.00)	(0.00)	(0.03)
Most Dynamic	-2.60	-2.60	-1.23	-1.04	-0.38	2.02	2.90	3.58	9.21	9.21
	(0.31)	(0.31)	(0.92)	(0.85)	(0.95)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
1 months<Effective Share Restriction<13 months										
Least Dynamic	-2.67	-2.32	-1.22	-0.90	-0.12	1.64	2.47	2.65	3.66	4.32
	(0.67)	(0.45)	(1.00)	(1.00)	(1.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
Moderately Dynamic	-3.67	-3.03	-1.34	-1.01	0.13	2.41	3.34	4.79	7.04	7.87
	(0.03)	(0.00)	(0.97)	(0.98)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Most Dynamic	-2.47	-2.47	-0.80	-0.53	-0.06	1.84	3.97	5.30	13.20	13.20
	(0.31)	(0.31)	(1.00)	(1.00)	(1.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
13 months=<Effective Share Restriction										
Least Dynamic	-2.87	-2.78	-1.58	-1.13	-0.24	1.45	2.55	3.02	4.16	4.33
	(0.41)	(0.13)	(0.73)	(0.90)	(1.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Moderately Dynamic	-2.20	-2.19	-1.53	-0.88	-0.02	1.77	2.90	3.60	5.09	6.75
	(0.86)	(0.57)	(0.81)	(0.99)	(1.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Most Dynamic	-2.57	-2.57	-1.88	-1.62	-0.19	2.28	3.51	4.82	7.21	7.21
	(0.19)	(0.19)	(0.31)	(0.15)	(1.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

Panel C. Regression of Alpha *t*-statistic on the Number of Change Points

	Intercept	Num. Change Points	mfee	ifee	Lockup	Notice	avglev	Adj_R^2
Estimate	0.53	0.21	0.00	-0.01	-0.01	0.01	0.00	0.05
t-value	2.81***	3.16***	0.00	-2.15**	-1.84*	6.19***	0.40	

Table VII. Sub-period Analysis on Performance and Dynamic Level

This table evaluates funds' portfolio performance before/during/post technology bubble period, consistent with Figure 1. The sub-period choice follows the breakdown used in Fung, Hsieh, Naik and Ramadorai (2008). The before technology bubble sub-period starts with January 1994 and ends with September 1998, the during technology bubble sub-period is October 1998 to March 2000 while the post technology bubble sub-period starts with April 2000 and ends with December 2009. Risk-adjusted performance is evaluated by fitting linear factor model with the five asset class factors. Estimates are presented; *, **, and *** indicate a significance level of 10%, 5%, and 1%, respectively.

	Int. (%)		Equity		Bond		Commodity		Currency		Credit		Adj.R^2
January 1994 to September 1998													
Least Dynamic	0.92		0.33	***	-0.10		0.09	**	-0.00		-0.42		0.56
Moderately Dynamic	3.55	**	0.29	***	-0.32	**	0.08	**	0.06		-1.96	**	0.58
Most Dynamic	4.95	**	0.45	***	-0.43	**	0.07		0.09		-3.03	**	0.58
October 1998 to March 2000													
Least Dynamic	8.97	*	0.27	*	-0.07		0.07		0.22		-3.48		0.11
Moderately Dynamic	8.66	**	0.21	*	-0.02		0.06		0.26		-3.22	*	0.20
Most Dynamic	13.84	***	0.31	***	-0.22		0.03		0.53		-5.61	***	0.49
April 2000 to December 2009													
Least Dynamic	0.13		0.19	***	0.03		0.06	***	-0.29	***	0.11		0.59
Moderately Dynamic	0.42		0.20	***	0.09		0.08	***	-0.20	**	-0.01		0.63
Most Dynamic	0.49		0.14	***	0.06		0.07	***	-0.19	**	-0.05		0.52

Table VIII. Fund Flow and Dynamics

Table VIII Panel A presents annual investor flows by dynamic level from 1995 to 2009. Monthly net flows for each hedge fund are computed as in equation (2) following Naik, Ramadorai and Stromqvist (2007). Then flows are aggregated across funds within the same dynamic level; the left panel of Panel A gives the results on this aggregated net flow in billion dollars. For better comparison across dynamic levels, the net flow number in the left panel is scaled over the aggregated AUM (asset under management) at year-end of the previous year; the scaled flow ratio is presented in the right panel in percentage. Table VIII Panel B presents the cross-sectional distribution of Bivariate Granger Causality Test Results. The question of interest is whether or not flow helps forecast return; it should do if hedge fund returns are diminishing in scale. The test involves using F-tests to test whether lagged information on flow provides any statistically significant information about return in the presence of lagged return. Particularly, we follow a simple approach by using the autoregressive specification of a bivariate vector autoregression assuming an autoregressive lag length 3.

$$R_t = intercept + a_1 R_{t-1} + a_2 R_{t-2} + a_3 R_{t-3} + b_1 F_{t-1} + b_2 F_{t-2} + b_3 F_{t-3}, \qquad H_0: b_1=b_2=b_3=0$$

Considering that with lagged returns, as in our regressions, the test is valid only asymptotically; our p_values are derived from the asymptotically equivalent chi-square test. In Panel B, the percentiles are determined by the p_values of the chi-square tests, which are reported in percent (%) in the parenthesis. The estimates included in Panel B are rescaled $(b_1+b_2+b_3)/3$ of the matching fund; in case there is no observation exactly matches the percentile p_values, we report the estimate of the closest match.

Panel A. Fund Flow at Each Dynamic Level

	Aggregate Net Flow ($bn.)			Aggregate Flow Ratio (%)		
Year	Least	Moderate	Most	Least	Moderate	Most
1995	0.09	0.00	0.05	18.27	29.43	57.17
1996	0.02	0.10	0.21	0.28	178.32	149.05
1997	-0.39	0.93	0.72	-3.17	44.89	55.84
1998	1.25	1.15	-0.90	7.79	38.24	-25.94
1999	-0.26	0.64	-0.34	-1.39	11.72	-14.71
2000	-1.28	0.05	0.46	-4.89	0.77	16.54
2001	5.15	3.54	0.71	14.30	22.17	19.76
2002	2.70	3.14	0.34	5.78	16.48	3.96
2003	11.56	8.89	0.52	19.64	34.31	5.20
2004	21.67	15.72	5.81	24.98	36.42	41.39
2005	10.50	-3.99	1.45	8.84	-5.54	5.90
2006	9.09	2.27	2.01	6.52	2.98	6.47
2007	7.84	10.35	8.24	4.92	12.73	24.83
2008	-9.48	-9.13	-5.02	-5.96	-9.17	-11.47
2009	-9.09	-12.87	-9.71	-6.76	-23.29	-34.62

Table VIII. (Cont.)

Panel B. Cross-Sectional Distribution of Bivariate Granger Causality Test									
	Min	5%	10%	25%	50%	75%	90%	95%	Max
January 1994 to September 1998									
Least	-0.14	-6.98	-0.09	-5.02	-0.03	0.05	-0.01	-0.01	-0.01
	(0.00)	(0.00)	(0.00)	(10.28)	(21.52)	(42.27)	(61.01)	(61.01)	(61.01)
Moderately	-2.13	-5.31	-0.14	-0.58	-0.22	0.00	-0.03	-0.87	0.00
	(0.00)	(0.00)	(0.00)	(0.02)	(6.59)	(26.95)	(48.52)	(52.62)	(98.16)
Most	-0.50	0.01	-0.16	0.76	-0.28	-1.09	0.12	16.28	16.28
	(0.00)	(0.00)	(0.00)	(0.00)	(0.30)	(9.70)	(17.98)	(47.57)	(47.57)
October 1998 to March 2000									
Least	0.29	0.29	0.29	0.29	0.51	0.51	0.51	0.51	0.51
	(9.60)	(9.60)	(9.60)	(9.60)	(46.88)	(84.16)	(84.16)	(84.16)	(84.16)
Moderately	-3.67	-3.67	10.66	-0.73	-1.34	0.95	-3.20	-3.20	-3.20
	(0.00)	(0.00)	(0.00)	(0.00)	(0.03)	(9.03)	(9.14)	(9.14)	(9.14)
Most	-0.39	-0.08	-0.93	-0.05	-1.94	-0.01	1.53	0.00	0.01
	(0.00)	(0.00)	(0.00)	(0.00)	(0.66)	(8.37)	(64.40)	(67.13)	(78.77)
April 2000 to December 2009									
Least	-0.03	-2.58	2.96	0.15	-0.57	-0.52	-0.51	-0.51	-0.51
	(0.00)	(0.00)	(0.00)	(0.13)	(4.84)	(28.32)	(61.54)	(61.54)	(61.54)
Moderately	0.03	0.03	0.03	0.03	7.99	-0.02	-0.02	-0.02	-0.02
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.16)	(0.16)	(0.16)	(0.16)
Most	-0.03	-0.03	-0.03	-0.03	-0.03	13.64	13.64	13.64	13.64
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

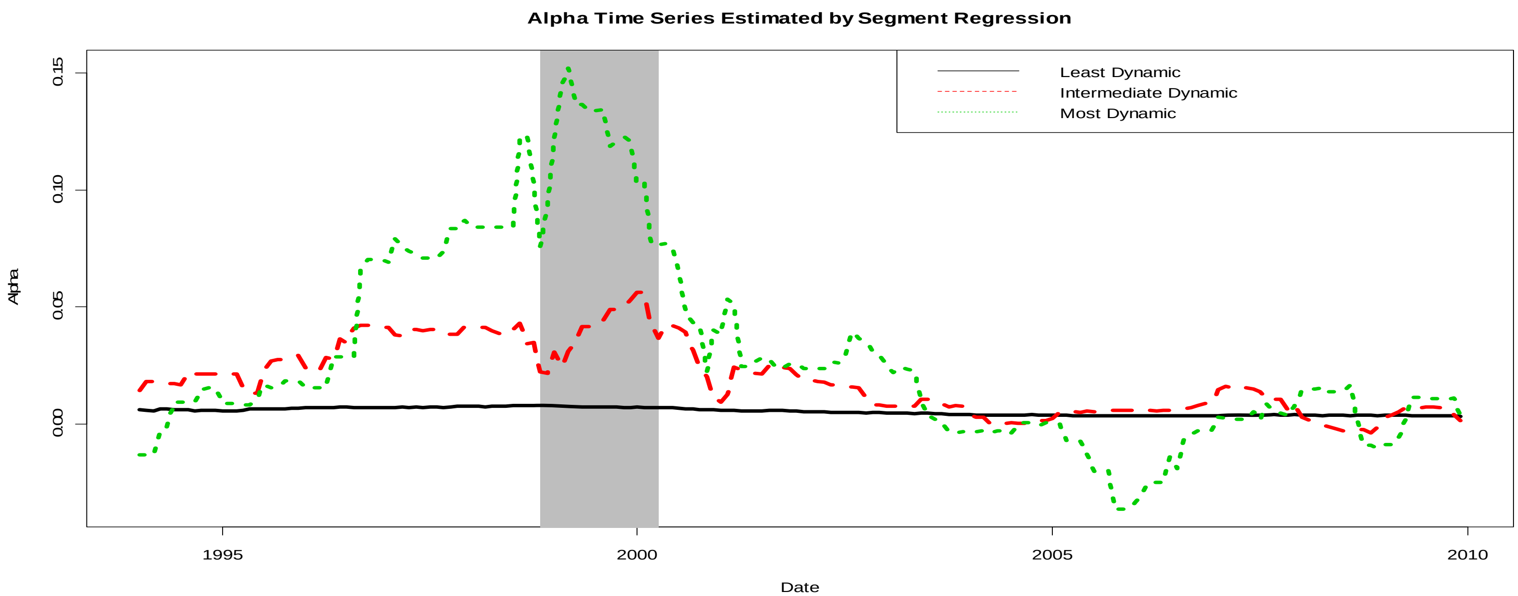

Figure 1.The Time Series Plot of Alpha for the Period of January 1994 to December 2009: The figure shows the re-evaluation of each hedge fund by conducting segment regression breaking at the estimated change dates. The average alpha is taken cross funds at each dynamic level and the time series of alpha is plotted for all three dynamic levels. The gray area corresponds to the during technology bubble period of October 1998 to March 2000; according to Fung, Hsieh, Naik and Ramadorai (2008), this is the only sub-period in which the average fund-of-funds delivers alpha.

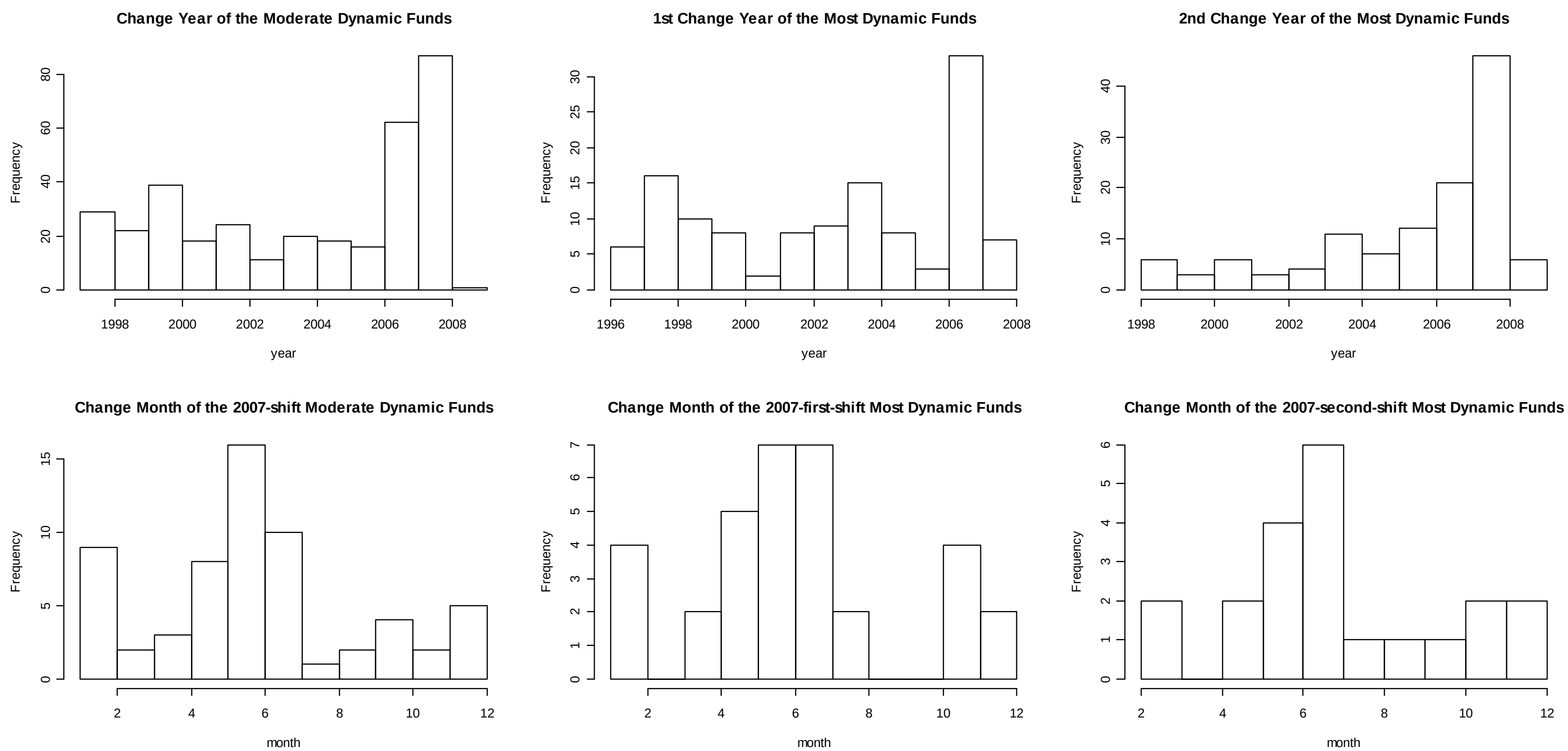

Figure 2. Shift-Date Histograms. Shift-date is estimated by minimizing sum square of residuals for each fund. This figure gives details in the distribution of the estimated shift dates. Three histograms in the first row present the distribution of shift-year for moderate-dynamic funds (the left one) and most-dynamic funds (the right two). Three histograms in the second row present the distribution of shift-month for the 2007-shifts, the left one is for the moderate-dynamic funds and the right two are for the most-dynamic funds.

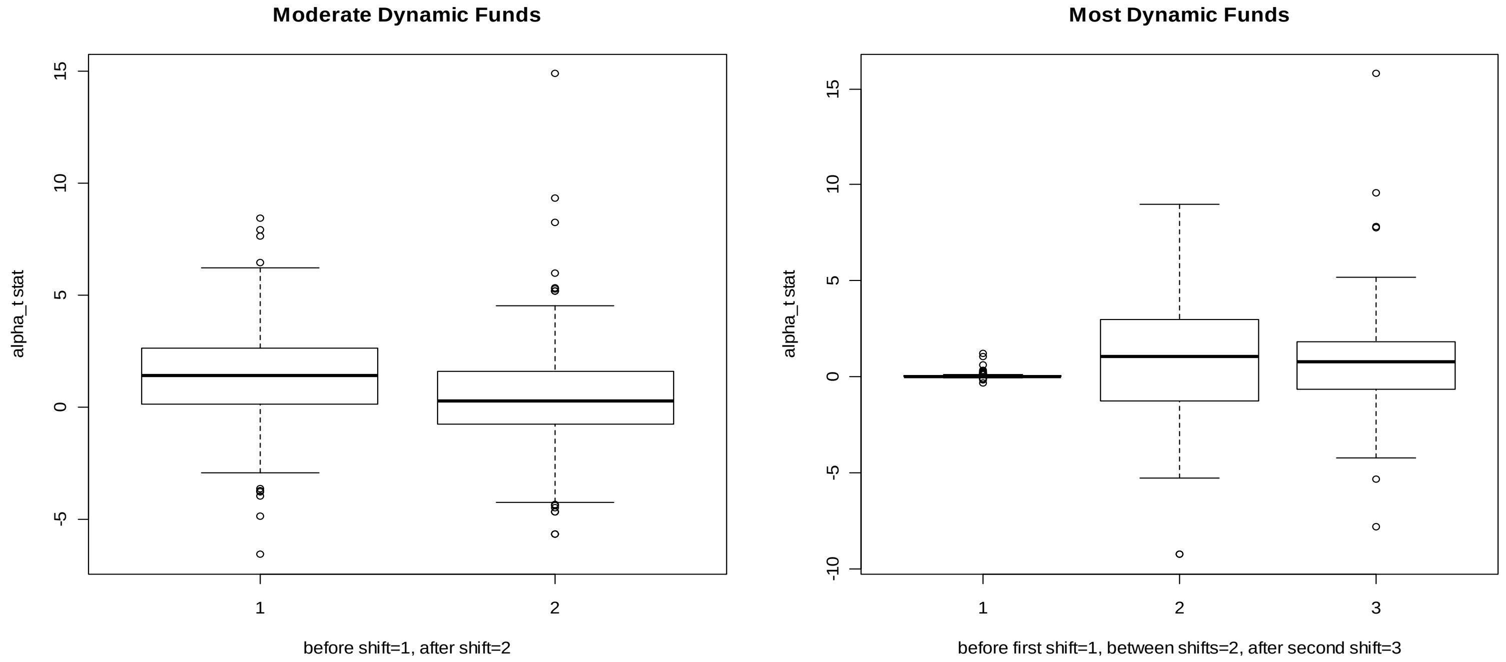

Figure 3. Change in Alpha around the Shift Event. This figure compares alpha before-the-shift and after-the-shift by box plots. The left plot is drawn on the two sub periods for each moderate-dynamic fund. The right plot is drawn on the three sub periods for each most-dynamic fund.