On the Dynamics of Hedge Fund Risk Exposures*

Andrew J. Patton† Tarun Ramadorai‡

Duke University University of Oxford

18 November 2009

Abstract

We propose a new method to capture changes in hedge funds' exposures to risk factors, exploiting information from relatively high frequency conditioning variables. Using a consolidated database of nearly 10,000 individual hedge funds between 1995 and 2008, we find substantial evidence that hedge fund risk exposures vary significantly across months. Our new method also reveals that hedge fund risk exposures vary within months, and capturing this variation significantly improves the fit of the model. The proposed method outperforms an optimal changepoint approach to capturing time-varying risk exposures, and we find evidence that there are gains from combining the two approaches. We find that the cost of leverage, movements in the VIX, and recent performance are the most important drivers of changes in hedge fund risk exposures.

Keywords: beta, time-varying risk, performance evaluation, structural breaks.

JEL Codes: G23, G11, C22.

---

*We thank the Oxford-Man Institute of Quantitative Finance for financial support, Alexander Taylor for dedicated research assistance, and Kevin Sheppard, Melvyn Teo and seminar participants at the Oxford-Man Institute Hedge fund conference for useful comments.

†Department of Economics, Duke University, and Oxford-Man Institute of Quantitative Finance. 213 Social Sciences Building, Durham NC 27708-0097, USA. Email: andrew.patton@duke.edu.

‡Saïd Business School, CEPR, and Oxford-Man Institute of Quantitative Finance. Park End Street, Oxford OX1 1HP, UK. Email: tarun.ramadorai@sbs.ox.ac.uk.

1 Introduction

A significant amount of research has been devoted to understanding the risk exposures and trading strategies of hedge funds.[1] Recently, several authors have highlighted that static analysis of these risk exposures is likely to miss the rapid changes in hedge funds' strategies occasioned by their trading flexibility and variations in their leverage ratios (see Fung and Hsieh (2004), Agarwal, Fung, Loon, and Naik (2006) and Fung, Hsieh, Naik and Ramadorai (2008)). In a recent paper, Bollen and Whaley (2009) propose using optimal changepoint regressions to estimate structural breaks in hedge fund factor loadings, and find that this method offers a significant improvement in statistical performance relative to a static factor model for hedge fund returns. An alternative approach, employed by Mamaysky, Spiegel and Zhang (2007) for mutual funds and considered by Bollen and Whaley (2009) for hedge funds, is to use a Kalman filter-based model to track risk exposures as latent random variables.

One of the distinguishing features of hedge funds is the speed with which their positions are altered or turned over in response to changing market conditions. Previous approaches for capturing hedge funds' time-varying risk exposures are limited to tracking changes only at the monthly frequency, as this is the reporting frequency for all of the main hedge fund databases. However it is quite likely that a hedge fund's risk exposures change substantially within a month. We propose a new method to capture intra-month variation in hedge fund risk exposures, which uses as its starting point the widely-used Ferson and Schadt (1996) model to employ higher frequency conditioning information. To overcome the lack of high frequency data on hedge fund performance, we posit a daily factor model for returns and then aggregate it up to the monthly frequency for estimation. We are thus able to employ monthly returns data and daily factor returns series to shed light on higher frequency variation in hedge fund returns. Using simulations as well as daily indices of hedge fund returns, we demonstrate that this technique enables us to track the dynamics of daily variation in hedge fund risk exposures very precisely.

Employing returns data on a cross-section of 9,538 hedge funds and funds-of-funds over the period 1995 to 2008, we find that our proposed method performs very well at describing the

[1] See Fung and Hsieh (1997, 2004 a,b), Ackermann, McEnally and Ravenscraft (1999), Liang (1999), Agarwal and Naik (2004), Kosowski, Naik and Teo (2006), Chen and Liang (2007), Patton (2009) and Jagannathan, Malakhov and Novikov (2009) for a partial list of examples.

dynamics of hedge fund returns. In particular, we show that the proposed model generates R^2 statistics that are a substantial improvement over those estimated using the optimal changepoint approach of Bollen and Whaley (2009): the cross-sectional distribution of R^2s is shifted to the right by approximately 6%. We find that the inclusion of the higher frequency conditioning information is an important contributor to the performance of our model: when we estimate the model using only monthly conditioning variables, its performance is only slightly better than that of the changepoint regression model.[2] Furthermore, we almost *double* the number of funds for which statistically significant factor exposure variation is found when we include daily information as well as monthly information. Thus variations in hedge fund risk exposures appear to occur at both the monthly and intra-monthly frequencies.

We conduct a relatively wide search for conditioning variables that help us to capture daily variation in hedge fund risk exposures. As noted by Ferson and Schadt (1996), Sullivan, Timmermann and White (1999), Ferson, Simin and Sarkissian (2008) and others, incorrect inferences about the significance of the "best" model will be obtained if this search process is ignored; this is the classic data snooping problem. We follow Sullivan *et al.* and employ the bootstrap reality check of White (2000) to control for this search. For comparison, we report the results of "naïve" tests, which ignore the search across variables, and find large differences in the number of funds that exhibit apparent significant variation in factor exposure.

The advantages conferred by our approach are not merely statistical. Our model has the added benefit of aiding economic interpretation of the variation in factor loadings that we estimate. For example, we find that two out of the three most frequently selected interaction variables are LIBOR and changes in short-term interest rates. We interpret this as evidence of the significant impact on hedge fund risk exposures of variation in the costs of leverage. This adds to the growing evidence (Liang (1999) and Lo and Khandani (2007)) on the role that leverage plays in explaining hedge fund returns. We also find evidence that variations in VIX as well as daily and monthly liquidity (measured as the percentage turnover on the NYSE stock market) significantly impact hedge fund factor loadings. Our results are thus complementary to those of Cao, Chen and Liang (2009), who study hedge funds' liquidity timing abilities in-depth using the Ferson and Schadt (1996) methodology, and Aragon (2006) and Sadka (2009), who connect measures of liquidity to hedge

[2]This finding is related to that of Bollen and Busse (2005), who find that mutual funds do generate positive risk-adjusted performance, but that the interval over which they do so is very short-lived.

fund returns.

The outline of the paper is as follows. The remainder of this section situates our paper in the literature on the dynamic performance evaluation of managed investments. Section 2 describes our modelling approach and Section 3 describes the data used in our analysis. Section 4 presents analyses which verify that our proposed method works well in practice, and Section 5 presents our main empirical results. Finally, Section 6 concludes.

1.1 Related literature

Our paper contributes to the literature on dynamic performance measurement for actively managed investment vehicles. An intellectual predecessor of our approach is Ferson and Schadt (1996), who use well-known predictors of returns as proxies for publicly available information, and use these instruments to estimate an unconditional version of their conditional model for the performance evaluation of mutual funds.[3] Their model uses only monthly data, and is related to Jagannathan and Wang (1996), who focus on risk adjustments for equities rather than performance evaluation. They motivate their method using the example of a hypothetical manager who wishes to keep fund volatility stable over time in an economy in which expected excess market returns and market volatility jointly covary with economic conditions. Their insight is that unconditional performance evaluation of this manager will yield negative alpha estimates if the time-variation in fund risk exposures is not properly accounted for. Using their method, they overturn the conclusion that the alpha of the 67 mutual funds in their sample is negative; their conditional performance evaluation reveals that the performance of these funds over the 1968 to 1990 period is broadly neutral.[4] The conditioning information used by Ferson and Schadt is lagged one month so as to capture only predetermined information; the interpretation of the alphas that they estimate is as the excess return earned by managers over and above that which could be generated by a managed portfolio strategy that used only public information to generate returns. The approach in Ferson and Schadt (1996) is extended by Christophersen, Ferson and Glassman (1998) to include the possibility of

[3] Chen and Knez (1996), in a contemporaneous paper, derive related insights about conditional performance evaluation.

[4] The Ferson and Schadt result that measured performance looks *better* than the constant-parameter risk-adjusted performance is also true in our analysis of hedge fund performance in Section 5. However this finding must also be interpreted with reference to the timing literature, as discussed below, since we include contemporaneous variables in our regression.

time-variation in alpha. These authors detect performance persistence amongst the most poorly performing mutual funds with greater precision than static models.

An earlier set of related models also uses conditioning information to detect time-variation in managerial risk exposures, but with a somewhat different goal. Treynor and Mazuy (1966) proposed an extension to the standard single factor market model which included a quadratic term in an effort to detect whether fund volatility rose when the market was performing well. The quadratic regression can be also motivated using the model of Admati, Bhattacharya, Pfleiderer and Ross (1986), in which a successful market-timing fund manager receives a noisy signal about the one period ahead market return. Such quadratic regressions have also been used by Lehmann and Modest (1987) in the context of mutual funds, and by Chen and Liang (2007) to describe the market timing ability of hedge funds. The idea has also been generalized to consider private signals about market attributes such as future market liquidity (see Cao, Chen and Liang (2009)). Another popular timing specification is that of Henriksson and Merton (1981), who extend the standard single factor market model by including an interaction between the market return and an indicator variable for when the market return is positive. The distinguishing feature of this class of models relative to the conditional performance evaluation models discussed earlier is the use of contemporaneous information on the conditioning variables. As a consequence of the use of this information, these models have two measures of managerial ability. The first, which the literature commonly refers to as 'timing', is the coefficient on the interaction term between the factor and the contemporaneous variable representing the signal (in the case of pure market timing, the signal would just be the factor plus noise, giving rise to the quadratic model). The second is the intercept that comes from the unconditional estimation of the conditional model. This is no longer the only measure of performance, but rather the 'selectivity' of the fund.[5] Ferson and Schadt (1996) also combine their approach with the Treynor-Mazuy and Henriksson-Merton specifications, generating conditional versions of the market-timing models.

Our approach in this paper can be viewed as a conditional market-timing model, since we include both contemporaneous and lagged conditioning information in our specifications. In this sense, the

[5] Holdings-based performance evaluation approaches have also been used to separate timing ability from selectivity (See Daniel, Grinblatt, Titman and Wermers (1997), Chen, Jegadeesh and Wermers (2000), and Da, Gao and Jagannathan (2009)). Graham and Harvey (1996) use asset allocation recommendations in investment newsletters to evaluate whether they help investors to time the market.

intercepts which we estimate in the unconditional versions of our conditional models are, strictly speaking, 'selectivity' measures. However, there are other possible interpretations. Jagannathan and Korajczyk (1986) show that if the strategies followed by funds have option-like characteristics, timing regressions admit alternative interpretations. For example, positive estimated selectivity and negative estimated timing may simply be evidence that funds are following a strategy akin to writing covered call options.

There have been other attempts to combine monthly returns and intra-monthly information to ascertain the higher-frequency variation in risk factor loadings, following an influential paper by Goetzmann, Ingersoll and Ivkovic (2000), which shows that Henriksson-Merton timing measures estimated from monthly data are biased in the presence of daily timing ability. Goetzmann *et al.* attempt to correct for this bias by cumulating daily put values on the S&P 500 for each month in their sample, and incorporate it as an additional regressor in their market-timing specifications. Ferson and Khang (2002) also present a conditional version of the holdings-based performance evaluation method that avoids the Goetzmann *et al.* bias. Our approach provides a new alternative to the methods followed in these papers; we posit a daily model for hedge fund returns, which we time-aggregate and estimate at the monthly frequency. Our aggregation of a daily factor model up to a monthly model is similar in spirit to Ferson, Henry and Kisgen (2006), who study government bond funds and consider an underlying continuous-time process for the term structure of interest rates. We evaluate the performance of our method using both simulations as well as available daily data on hedge fund indices and find that it is successful at accurately capturing estimated daily risk exposures.

Our use of daily returns on hedge fund indices to validate our technique (see Section 4) adds to the sparse literature which uses daily data on investment managers' returns to measure their performance. Busse (1999) finds that mutual funds have significant volatility timing ability using daily returns data. Bollen and Busse (2001), also using daily data, confirm that mutual funds have significant market timing ability. Chance and Hemler (2001) use daily executed recommendations of market-timers, and find that they have significant daily timing ability which vanishes when their performance is evaluated at the monthly frequency.

Finally, in addition to Bollen and Whaley (2009), other papers in this area use a variety of innovative approaches to infer unobserved risk-taking: A recent example is Kacperczyk, Sialm and Zheng (2007), who use the difference between mutual fund holdings-based imputed returns and reported returns to predict future mutual fund returns. Mamaysky, Spiegel and Zhang (2007), cited above, allow betas to evolve as latent random variables and track their changes using the Kalman filter. The next section presents our method for modelling time-varying hedge fund exposures.

2 Modelling time-varying hedge fund risk exposures

A variety of methods have been proposed in the literature for capturing time-varying risk exposures of hedge funds, see Bollen and Whaley (2009) for a recent review. In this section we first describe the modelling approach advocated by Bollen and Whaley (2009), an "optimal changepoint" model, and then introduce our method to capture time-variation in factor loadings. To simplify the discussion of the various approaches we consider a simple one-factor model for capturing risk exposures, although in our empirical results in Section 5 we allow for multiple factors.

2.1 Changepoint models for hedge fund returns

A simple but effective approach for capturing dynamic hedge fund risk exposures used by Bollen and Whaley (2009) is optimal changepoint regression, see Andrews, *et al.* (1996). This approach models beta as constant between changepoints, with abrupt changes to a new value at the changepoints. The theory in Andrews, *et al.* (1996) allows the researcher to consider many changepoints but in the interests of parsimony Bollen and Whaley (2009) allow for the presence of just a single changepoint for each fund (although the time of the changepoint can differ across funds). Thus this model for hedge fund returns is:

$$r_{it} = \alpha_i + \alpha_i^0 \cdot \mathbf{1}\left(t \leq \tau_i^*\right) + \beta_i f_t + \beta_i^0 f_t \cdot \mathbf{1}\left(t \leq \tau_i^*\right) + \varepsilon_{it} \tag{1}$$

where r_{it} is the return on hedge fund i in month t, f_t is the return on the factor in month t, and $\mathbf{1}\left(t \leq \tau_i^*\right)$ is an indicator for whether the time period t is before the changepoint τ_i^*. Testing for the significance of the change in risk exposures in a changepoint regression is complicated by the fact that the *date* of the change, τ_i^*, is estimated at the same time as the pre- and post-change parameters. Having searched across all possible dates for the most likely date of a change, it is no longer appropriate to use a standard F-test to test for the significance in the change in the parameters. Instead, non-standard asymptotic critical values or bootstrap critical values must be used to determine the significance of the change. We describe a bootstrap approach in Section 2.4

below.

2.2 Models with monthly variation in risk exposures

A simple but economically interpretable alternative to the change-point approach discussed above is a model for time-varying betas based on observable conditioning variables, which as discussed above is used by Ferson and Schadt (1996) for mutual funds, and by Cao, *et al.* (2009) in their study of hedge fund liquidity. In this approach, the betas are specified to evolve as a linear function of observable variables measured monthly:

$$\begin{aligned} r_{it} &= \alpha_i + \beta_{it} f_t + \varepsilon_{it} \\ \text{where} \quad \beta_{it} &= \beta_i + \gamma_i Z_t \end{aligned}$$

That is, the return on fund i is driven by a factor, f_t, with the factor loading varying according to some zero-mean variable Z_t.[6] Substituting in the model for β_{it} we obtain the following:

$$r_{it} = \alpha_i + \beta_i f_t + \gamma_i f_t Z_t + \varepsilon_{it} \tag{2}$$

which is easily estimated using OLS regression (although standard errors that are robust to heteroskedasticity and non-Normality should be used in place of the usual OLS standard errors, to account for these features of hedge fund returns). Note that the constant-beta model is nested in the above specification, and the significance of time variation in beta for the i^{th} fund can be tested via a standard Wald test of the following hypothesis:

$$H_0^{(i)} : \gamma_i = 0 \quad \text{vs.} \quad H_a^{(i)} : \gamma_i \neq 0 \tag{3}$$

As discussed above, Ferson and Schadt (1996) find that capturing variation in risk exposures via observable variables at the monthly frequency improves the accuracy of factor models such as those above. Mamaysky, *et al.* (2008) also find that adding observable variables to their model for mutual fund returns improves its performance, relative to a model solely with a latent factor driving variation in risk exposures. Cao, *et al.* (2009) find that monthly measures of liquidity are able to explain some of the changes in the market exposures of hedge funds.

[6] The distinction between using Z_t and Z_{t-1} is discussed in detail in Section 1.1.

2.3 Models with *daily* variation in risk exposures

As mentioned earlier, one of the distinguishing features of hedge funds, compared with other asset managers, is the speed with which positions are altered or turned over. Thus, unlike mutual funds for example, it is likely that a hedge fund's risk exposures change substantially within a month. This observation necessitates an extension of the above approach to modelling time-varying risk exposures. Consider the daily returns on hedge fund i, denoted r^*_{id}, and a corresponding daily factor model for these returns:

$$r^*_{id} = \alpha_i + \beta_{id} f^*_d + \varepsilon^*_{id}$$

Let us assume that the factor loadings for this fund vary as a function of some factor, Z, which is observable at a daily frequency. Let Z^*_d denote this variable measured at the daily frequency and Z_t denote this variable measured at the monthly frequency (that is, Z_t will be constant within each month and jump to a new level at the start of each month).

$$\beta_{id} = \beta_i + \gamma_i Z_t + \delta_i Z^*_d$$

Substituting in we obtain a simple interaction model for daily hedge fund returns:

$$r^*_{id} = \alpha_i + \beta_i f^*_d + \gamma_i Z_t f^*_d + \delta_i Z^*_d f^*_d + \varepsilon^*_{id} \tag{4}$$

Returns on individual hedge funds are currently only available monthly, and so to estimate this model we need to aggregate returns from the daily frequency up to the monthly frequency. Define the monthly return on fund i as:

$$r_{id} \equiv \sum_{j=1}^{n} r^*_{i,d+1-j}, \text{ for } d = n, 2n, 3n, ...$$

where n is the number of days in month t, and similarly for f_t and Z_t.[7] Then the specification for monthly hedge fund returns becomes:

$$r_{it} = n\alpha_i + \beta_i f_t + \gamma_i Z_t f_t + \delta_i \sum_{j=1}^{n} Z^*_{22t-j} f^*_{22t-j} + \varepsilon_{it} \tag{5}$$

Note that the dependent variable above is now the monthly return on hedge fund i, and all variables on the right-hand side are also measured monthly. The new variable that appears in this specification relative to the Ferson-Schadt style specification discussed in the previous section is of the

[7] Of course, the number of trading days in each month varies and so should more accurately be denoted n_t. We omit the subscript t for simplicity.

form $\sum Z_d^* f_d^*$. This is a monthly aggregate of a *daily* interaction term, and it captures variations in hedge fund risk exposures at the daily frequency. (Ferson, Henry and Kisgen (2006) also obtain a monthly aggregate factor in their study of bond fund performance.) If the factor, f_d^*, and the conditioning variable, Z_d^*, are both available at the daily frequency, then under the assumption that ε_{id}^* is serially uncorrelated and uncorrelated with f_s^* for all (d, s) we are able to estimate the coefficients of this model using standard OLS. As above, for valid statistical inference we need to account for potential heteroskedasticity and non-normality in the residuals. In Section 4 we present analyses based on real daily hedge fund index returns and on simulated returns that confirm that this modeling approach works well in realistic applications.

The constant-beta model is nested in the above specification, and the significance of time variation in beta can be tested via a standard Wald test of the following hypothesis:

$$H_0^{(i)} : \gamma_i = \delta_i = 0 \quad \text{vs.} \quad H_a^{(i)} : \gamma_i \neq 0 \cup \delta_i \neq 0 \tag{6}$$

Furthermore, we can test whether we find significant evidence of daily variation in hedge fund risk exposures, controlling for monthly variation, by testing that the coefficient on the daily interaction term is zero:

$$H_0^{(i)} : \delta_i = 0 \quad \text{vs.} \quad H_a^{(i)} : \delta_i \neq 0 \tag{7}$$

While it is anticipated that hedge funds do adjust their risk exposures within the month, our ability to detect those changes depends on whether we can find observable daily factors, f_d^*, that are correlated with those changes.

2.4 Bootstrap tests

Inference on the above models involves non-standard econometric methods. The optimal changepoint model is estimated by searching over all possible dates for the changepoint, invalidating standard F-tests for the significance of the changepoint. As discussed in detail in Section 3 below, the models based on observable conditioning information also involve searches, this time across an array of possible conditioning variables. The approach of searching for the best-fitting conditioning variable and then testing its significance via a standard F-test suffers from data snooping bias, see White (2000) for example. To obtain valid critical values for tests for these models we employ a bootstrap approach.

2.4.1 Testing the significance of the changepoint

To test the significance of the optimal changepoint, we use a parametric bootstrap with samples drawn according to the stationary bootstrap of Politis and Romano (1994). To bootstrap data under the null hypothesis of no significant changepoint we first estimate the constant-parameter factor model on a hedge fund's returns, and save the estimated parameter vector and the regression residuals. We then create bootstrap samples of returns for this hedge fund imposing the null of no change in the parameter vector

$$r_{i,s_b(t)}^{(b)} \equiv \hat{\alpha}_i + \hat{\beta}_i f_{s_b(t)} + \varepsilon_{i,s_b(t)}$$

where $(\hat{\alpha}_i, \hat{\beta}_i)$ are the parameter estimates from the original data, b is an indicator for the bootstrap number (running from $b = 1$ to B) and $s_b(t)$ is the new time index which is a random draw from the original set $\{1, .., T\}$. Serial dependence in returns is captured by drawing returns data in blocks with starting point and length both random. Following Politis and Romano (1994), the block length is drawn from a geometric distribution, with a parameter q_{SB} that controls the average length of each block. In our empirical work we set $q_{SB} = 3$. Each bootstrap sample is the same length as the original sample for the fund. For each set of bootstrapped data we compute the "*avgF*" statistic of Andrews, *et al.* (1996).[8] The 90^{th} percentile of the distribution of this statistic across the $B = 1,000$ bootstrap samples serves as the 0.10 level critical value for the test of no significant changepoint. If the *avgF* statistic for a given fund is larger than this fund-specific critical value, then we have significant evidence of a change in the parameters of this model for that fund.

2.4.2 Controlling for the search across potential conditioning variables

As noted by Ferson and Schadt (1996), Sullivan, Timmermann and White (1999), and Ferson, Simin and Sarkissian (2008), it is critical to take into account the search across potential conditioning variables when conducting tests of the significance of the "best" model. We follow Sullivan, *et al.* (1999) and test the significance of the best-fitting conditioning variable by using the "reality check" of White (2000), again employing the stationary bootstrap of Politis and Romano (1994). The test statistic for this approach is the smallest p-value, across all potential conditioning variables, from a joint test of the significance of all coefficients on interaction variables, as in the hypotheses

[8] In our empirical work we also computed the "*supF*", and "*expF*" statistics and found little difference in the results of the tests when applied to our hedge fund data.

in equation (6). To obtain critical values that are valid in the face of our search across many possible interaction variables we bootstrap both the hedge fund return and the factor returns, and estimate the interaction model in equation (5). To impose the null hypothesis that the interaction terms have zero coefficients, we then re-center the parameters estimated on the bootstrap data by subtracting the actual estimated values of these parameters. We then compute p-values for the joint test of significance of the interaction terms, and store the smallest of these across all interaction variables considered. The 10^{th} percentile of the distribution of this statistic across the $1,000$ bootstrap samples serves as the 0.10 level critical value for the test of no significant interaction variables. If the smallest p-value observed on our real data is smaller than this critical value then we have evidence of a significant interaction variable, controlling for our search across many possible variables.

3 Data

3.1 Hedge fund and fund of funds data

We use a large cross-section of hedge funds and funds-of-funds over the period from 1995 to 2008, which is consolidated from data in the HFR, CISDM and TASS hedge fund databases. The appendix contains details of the process followed to consolidate these data. The funds in the combined database come from a broad range of vendor-classified strategies, which are consolidated into nine main strategy groups: Security Selection, Global Macro, Relative Value, Directional Traders, Funds of Funds, Multi-Process, Emerging Markets, Fixed Income, and Other. Table A.1. in Appendix A shows the mapping from the vendor classifications to these nine strategy groups. The set contains both live and dead funds, the percentage of the funds in the data that are live and dead is reported in Table A.2. in the Appendix. The distribution of live versus defunct funds is roughly similar across the databases, and the total percentage of defunct funds is 46%, which is comparable to the ratio reported in Agarwal, Daniel and Naik (2009) of 48%, although their sample period ends in 2002.

Table 1 reports summary statistics on the hedge fund data. To overcome the well-known problem of return smoothing in monthly reported hedge fund returns, we use "unsmoothed" returns in our analysis, which are estimated from the raw returns using the Getmansky, Lo and Makarov (2004) moving average model. The parameters of this model are estimated separately for each individual fund, and as in Getmansky, *et al.* (2004) we use two lags. The means of the reported returns and unsmoothed returns are similar, but as expected the distribution of the "unsmoothed" returns is slightly more disperse.[9] The median fund has assets under management of USD 32MM, while the mean is much larger, at USD 167MM, reflecting the significantly skewed size distribution that several other studies (Getmansky (2005), Teo (2009)) have highlighted. The median management fee is 1.5%, and the median incentive fee is 20%, consistent with earlier literature (Agarwal, Daniel and Naik (2009)); and the withdrawal restrictions (lockup & redemption notice periods) are also comparable to earlier literature (Aragon (2006)). Panel B of the table shows that the lengths of the return histories for the funds in the sample correspond closely to that reported by Bollen and Whaley (2009), with around half of our funds having 5 or more years of data available, and around 17% of our funds having less than 3 years of data. The mean and median sample sizes across all funds in our study are 62 and 51 observations respectively. Finally, Panel C reports the distribution of funds across strategies: the two largest strategies are Security Selection (28.7%) and Funds of Funds (22.2%), while the two smallest strategies are Relative Value (3.3%) and Global Macro (6.0%), similar to that reported in Ramadorai (2009). Given that our complete sample contains 9,538 individual funds, even the smallest strategy group has 312 distinct hedge funds, which enables us to undertake relatively precise strategy-level analyses.

3.2 Hedge fund factors

The second set of data that we employ is on factor returns. Throughout our analysis, we model the risks of hedge funds using the seven-factor model of Fung and Hsieh (2004a). These seven factors have been shown to have considerable explanatory power for fund-of-fund and hedge fund returns, see Fung and Hsieh (2001,2002,2004a,b), and have been used in numerous previous studies, see Bollen and Whaley (2009), Teo (2009) and Ramadorai (2009). The set of factors comprises the excess return on the S&P 500 index (SNPMRF); a small minus big factor (SCMLC) constructed as the difference between the Wilshire small and large capitalization stock indices; the excess returns on portfolios of lookback straddle options on currencies (PTFSFX), commodities (PTFSCOM), and bonds (PTFSBD), which are constructed to replicate the maximum possible return to trend-

[9] The use of reported returns does not qualitatively affect the results that we report in this paper.

following strategies on their respective underlying assets;[10] the yield spread of the U.S. 10-year Treasury bond over the 3-month T-bill, adjusted for the duration of the 10-year bond (BD10RET); and the change in the credit spread of Moody's BAA bond over the 10-year Treasury bond, also appropriately adjusted for duration (BAAMTSY).

3.3 Variables associated with changes in risk exposures

We consider a variety of different variables that may be associated with hedge fund managers' decisions to increase or decrease their exposure to systematic risks. These variables can be categorized into four broad groups, corresponding to the underlying drivers of liquidity, funding and leverage, sentiment and performance.

3.3.1 Liquidity factors

There is a growing recognition of the impact of liquidity on hedge fund and mutual fund performance. Pollet and Wilson (2008) document that mutual funds rarely diversify in response to increases in their asset base, and associate their result with limits to the scalability of fund portfolios, such as price impact or liquidity constraints. Sadka (2009) finds that liquidity risk is an important determinant of hedge fund returns, and one that is not captured by the Fung-Hsieh (2004a) seven factors.

Following the recent work of Cao, *et al.* (2009) we consider the case that managers may attempt to time their exposure to risk factors in such a manner as to mitigate the influence of price impact. As liquidity rises (falls), the absolute magnitude of risk exposures will rise (fall) as funds more (less) frequently enter or exit positions. This feature is documented in Cao, *et al.* (2009) for hedge fund exposures to the CRSP value-weighted index, and we also consider it, amongst other possible conditioning variables, for the other Fung-Hsieh hedge fund factors. To capture systematic time-series variation in asset market liquidity at both monthly and daily frequencies we employ NYSE turnover, measured as the ratio of the aggregate volume traded in dollars each day or month, divided by the aggregate market capitalization of the stocks at the close of the day or month, and detrended using an exponentially weighted moving average. Griffin, Nardari and Stulz (2007)

[10] See Fung and Hsieh (2001) for a detailed description of the construction of these primitive trend-following (PTF) factors.

employ a similar measure of liquidity, and Hasbrouck (2009) provides evidence that volume-based liquidity measures are able to capture time-variation in liquidity better than price-based measures.

3.3.2 Funding and leverage

Mechanically, hedge fund managers' exposures to systematic risk factors will vary with the level of leverage that they employ, if their long and short positions do not exactly offset one another along the dimension of factor exposure (see Rubin, Greenspan, Levitt and Born (1999) who document that hedge funds take on significant leverage). The leverage available to hedge funds will vary with the costs of borrowing, which we capture using several measures. First, we include both contemporaneous and lagged LIBOR rates, and contemporaneous and lagged certificate of deposit secondary market rates (the latter as a proxy for the one-month T-bill rate, but with the added benefit of daily data availability). We then compute level (the constant maturity three month T-bill rate), slope (the difference between the ten-year T-bond and three month T-bill rates) and curvature (twice the two-year rate less the three-month rate less the ten-year rate) factors for the U.S., and use their first differences as conditioning variables. Finally, to capture variation in the availability of credit on account of changes in the probability of default, we include the level of the credit spread of Moody's BAA bond over the 10-year Treasury bond, adjusted for duration.

3.3.3 Sentiment

Brunnermeier and Nagel (2004) point out that hedge funds "rode" the technology bubble of the late 1990s, going long as technology stock prices rose. They also document that hedge funds skillfully cut back their exposures just prior to the NASDAQ crash of 2000. This evidence is borne out by the analysis of Fung, Hsieh, Naik and Ramadorai (2008), who highlight that the only period during which the average fund generated statistically significant alpha was during the peak of the internet bubble. We therefore include several proxies for investor sentiment, with the view that if this mechanism is in operation, hedge funds will increase their risk exposures as investor sentiment rises and vice versa. The proxies we employ are the VIX index (demeaned using an exponentially weighted moving average), which is labelled the market's 'fear gauge' in Whaley (2000), and the University of Michigan's consumer sentiment index, which has been employed as a sentiment proxy in several studies, see Lemmon and Portniaguina (2006) and Qiu and Welch (2006) for two recent examples.

3.3.4 Performance

Several papers on hedge funds have debated the role of incentive-alignment mechanisms such as high-water marks on hedge fund risk-taking behavior. When a fund makes low or negative returns, it is more likely to be under its high-water mark, and consequently, managers may have incentives to increase their levels of systematic risk (see Goetzmann, Ingersoll and Ross (2003)) and vice versa.[11] We therefore include the fund's recent performance (past one-month and past three-month returns) as conditioning variables. Furthermore, hedge fund managers are often implicitly or explicitly benchmarked to commonly available indices. When S&P 500 returns are high, managers may be tempted to increase their risk-factor loadings to avoid the perception that they are underperforming. With this in mind, we also include both contemporaneous and lagged returns on the S&P 500 as possible conditioning variables in our setup.

All told, we have a set of 22 possible conditioning variables in our set: Turnover, Lagged Turnover, Certificate of Deposit 1M, Lagged Certificate of Deposit 1M, ΔLevel, ΔSlope, ΔCurvature, Lagged ΔLevel, Lagged ΔSlope, Lagged ΔCurvature, Default Spread, Lagged Default Spread, LIBOR, Lagged LIBOR, VIX, Lagged VIX, Michigan Sentiment, Lagged Michigan Sentiment, Fund Performance (last month), Fund Performance (last quarter), S&P 500 Return, Lagged S&P 500 Return.

4 The accuracy of estimates of daily variations in beta using monthly returns

In this section we study the accuracy of our proposed method for estimating daily variations in the factor exposures of hedge funds using only monthly returns on these funds. We analyze this problem in two ways, and we find support for our method in both cases. Data on individual hedge fund returns is almost invariably available only at the monthly frequency, however daily data on a collection of hedge fund style index returns has recently become available. These daily index returns are an ideal, real-world dataset on which to check the accuracy of our method. Our first approach is to employ this daily data on hedge fund index returns, and to compare the results that are obtained when estimating the model on daily data with those that are obtained when only

[11] Note that Panageas and Westerfield (2009) analyze high water mark contracts as a sequence of options with a changing strike price, and do not find risk-shifting problems in their setup.

using monthly returns on these indices. Second, we conduct a simulation study that is calibrated to match the key features of hedge fund returns, and study the accuracy of the proposed method in this setting. In this analysis we check the robustness of our estimation method to different features of the return-generating process.

4.1 Results using daily hedge fund index returns

Daily returns on hedge fund style indices have recently become available from Hedge Fund Research (HFR)[12]. We use these data to check whether the estimates of hedge fund factor exposures that we obtain using our method, based on only monthly returns, are similar to those that would be obtained if daily data were available. As the HFR daily returns are only available at the index level and begin only in April 2003, they are not a replacement for the comprehensive data that we employ on individual hedge funds. Nevertheless this daily information provides us with valuable insights into the performance of our method.

We employ the daily HFR indices for five hedge fund styles: equity hedge, event driven, convertible arbitrage, merger arbitrage, and market neutral. The period April 2003 to October 2008 yields 1409 daily observations and 67 monthly observations. In our main empirical analysis in Section 5 below, we consider the seven-factor Fung-Hsieh model for hedge fund returns, but three of the Fung-Hsieh factors (the returns on three portfolios of lookback straddle options) are only available at a monthly frequency, and so they are not suitable for our model of daily hedge fund index returns. Thus we restrict our attention to the four Fung-Hsieh factors that are available at the daily frequency. As in our main analysis below, we follow Bollen and Whaley (2009) and reduce the Fung-Hsieh model to a more parsimonious two-factor specification by using the Bayesian Information Criterion to find the two Fung-Hsieh factors that best describe the daily hedge fund index returns. The chosen factors and the coefficients on these factors in models using daily and monthly returns are presented in Table 2.

Table 2 reports the estimation results for the constant-beta factor model, using both daily and monthly hedge fund returns. This table confirms that estimating a constant-beta model using monthly returns data yields similar parameter estimates to those obtained using daily data[13]. As

[12] Distaso, *et al.* (2009) are perhaps the first to study the properties of these data.

[13] The alpha estimates presented in Table 2 are *daily* alphas, and so should be multiplied by approximately 22 to obtain monthly alphas.

expected, t-statistics are generally lower in the model estimated on monthly data, but the signs and magnitudes of the estimated parameters are generally close.

Table 3 presents the results of the model for time-varying factor exposures based on conditioning information, estimated either using daily returns or using monthly returns. The models that are estimated are:

$$r_{id}^{*} = \alpha_i + \beta_{i1} f_{1d}^{*} + \beta_{i2} f_{2d}^{*} + \gamma_{i1} f_{1d}^{*} Z_t + \gamma_{i2} f_{2d}^{*} Z_t + \delta_{i1} f_{1d}^{*} Z_d^{*} + \delta_{i2} f_{2d}^{*} Z_d^{*} + \varepsilon_{id}^{*} \quad (8)$$

$$\begin{aligned} r_{it} &= 22\alpha_i + \beta_{i1} f_{1t} + \beta_{i2} f_{2t} + \gamma_{i1} f_{1t} Z_t + \gamma_{i2} f_{2t} Z_t \quad (9) \\ &\quad + \delta_{i1} \sum_{j=1}^{n} f_{1,22t+1-j}^{*} Z_{22t+1-j}^{*} + \delta_{i2} \sum_{j=1}^{n} f_{2,22t+1-j}^{*} Z_{22t+1-j}^{*} + \varepsilon_{it} \end{aligned}$$

and so α_i is the daily alpha of the fund, β_{i1} and β_{i2} are the constant exposures to the two factors f_1 and f_2, γ_{i1} and γ_{i2} capture variations in factor exposures that occur at the monthly frequency (with the variable Z_t) and δ_{i1} and δ_{i2} capture variations in factor exposures that occur at the daily frequency (with the variable Z_d^{*}).

If the methodology presented in Section 2 is accurate, then we would expect to see similar parameter estimates across the two sampling frequencies. Up to sampling variability, this is indeed what we observe: Across all five indices, the signs of the estimated coefficients generally agree, and cases of disagreement tend to coincide with parameter estimates that are not significantly different from zero. As expected, the parameter estimates obtained from monthly returns are less accurate than those estimated using daily returns: averaging across all indices and all parameters, the t-statistics on the daily coefficients are 4.14 times larger for the daily model than for the monthly model, which is close to the ratio we would expect theoretically, $\sqrt{22} \approx 4.69$.

Table 3 also presents the correlation between the time series of daily factor exposures (betas) estimated using daily and monthly returns. For example, the correlation between the time series of daily exposure to the S&P500 of the equity hedge index estimated using daily and monthly returns is 0.98, and the correlation of daily estimates of this index's exposure to SMB is 0.85. Across the five indices and two factor exposures the average correlation is 0.75. The lowest value (0.25) occurs for the market neutral index, which was found to have no statistically significant variation in its factor exposures, and thus a low correlation coefficient is not surprising.

In Figures 1 and 2 we present an illustration of the correspondence between the estimates of daily factor exposures estimated using actual daily index returns, or using only monthly returns. For clarity, we narrow the focus of these plots to the first quarter of 2008 (the same conclusions are drawn from other periods). These figures illustrate the strong similarity between the two estimates of time-varying exposure to the S&P500 index, and provide further support for the modelling approach proposed in Section 2.

4.2 Results from a simulation study

Next, we consider a simulation study designed to further investigate the accuracy of our proposed estimation method. For simplicity, we consider a one-factor model for a hypothetical hedge fund, and as in our main empirical analysis below, we allow factor exposures to vary at both the daily and monthly frequencies. This yields a process for *daily* hedge fund returns as:

$$r_d^* = \alpha + \beta f_d^* + \gamma f_d^* Z_d + \delta f_d^* Z_d^* + \varepsilon_{R,d}^*, \quad d = 1, 2, ..., 22 \times T, \tag{10}$$

where $r_t \equiv \sum_{j=0}^{21} r_{22t-j}^*$, is the monthly equivalent of the daily variable in the above specification (analogously f_t, Z_t). The parameter β captures the average level of beta for this fund, γ captures variations in beta that are attributable to the monthly variable Z_t, and δ captures variations in beta that are attributable to the daily variable Z_d. If we aggregate this process up to the monthly frequency we obtain:

$$r_t = 22\alpha + \beta f_t + \gamma f_t Z_t + \delta \sum_{j=0}^{21} f_{22t-j}^* Z_{22t-j}^* + \varepsilon_{R,t}, \quad t = 1, 2, ..., T. \tag{11}$$

The parameters α, β and γ are all estimable using only monthly data; the focus of this simulation study is our ability to estimate δ, and whether attempting to do so adversely affects our estimates of the remaining parameters.

We next specify the dynamics and distribution of the factor and the conditioning variable. To allow for autocorrelation in the conditioning variable (as found in such variables as volatility and turnover) we use an AR(1) process for Z_d^* :

$$Z_d^* = \phi_Z Z_{d-1}^* + \varepsilon_{Z,d}^*$$

The conditioning variable is de-meaned prior to estimation, and so the omission of an intercept in the above specification is without loss of generality. We also assume an AR(1) for the factor returns, to allow for the possibility that these are also autocorrelated:

$$f_d^* = \mu_F + \phi_F \left(f_{d-1}^* - \mu_F\right) + \varepsilon_{F,d}^*$$

Finally, we assume that all innovations are normally distributed, and we allow for correlation between the factor innovations and the innovations to the conditioning variable:

$$\left[\varepsilon^*_{R,d}, \varepsilon^*_{F,d}, \varepsilon^*_{Z,d}\right]' \sim N\left(\left[\begin{array}{c} 0 \\ 0 \\ 0 \end{array}\right], \left[\begin{array}{ccc} \sigma^2_{\varepsilon R} & 0 & 0 \\ \cdot & \sigma^2_{\varepsilon F} & \rho_{FZ}\sigma_{\varepsilon F}\sigma_{\varepsilon Z} \\ \cdot & \cdot & \sigma^2_{\varepsilon Z} \end{array}\right]\right)$$

To obtain realistic parameter values for the simulation we calibrate the model to the results obtained when estimating the model using daily HFR index returns. We use the equity hedge index, with the S&P500 index as the factor and the VIX volatility series as the conditioning variable. This leads to the following parameters for our simulation:

$$\begin{aligned} \alpha &= 2/(22 \times 12),\ \beta = 0.4,\ \gamma = 0.002,\ \delta = -0.004 \\ \mu_F &= 10/\left(22 \times 12\right),\ \sigma_F = 20/\sqrt{22 \times 12},\ \sigma_Z = 10,\ \sigma_{\varepsilon F} = \sqrt{0.1} \end{aligned}$$

Thus we assume that the fund generates 2% alpha per annum with an average beta of 0.4, and a daily beta that varies with both daily and monthly fluctuations in the conditioning variable $(Z^*$ and $Z)$. The factor is assumed to have an average return of 10% per annum and an annual standard deviation of 20%. The conditioning variable has daily standard deviation of 10 (similar to the VIX), and the innovation to the returns process has a daily variance of 0.1, which corresponds to an R^2 of around 0.6 in this design.

We vary the other parameters of the returns generating process in order to study the sensitivity of the method to these parameters. We consider:

$$\begin{aligned} \phi_Z &\in \{0, 0.5, 0.9\} \\ \phi_F &\in \{-0.2, 0, 0.2\} \\ \rho_{FZ} &\in \{0, 0.5\} \\ T &\in \{24, 60, 120\} \end{aligned}$$

Thus we allow the conditioning variable to vary from *iid* $(\phi_Z = 0)$ to persistent $(\phi_Z = 0.9)$, we allow for moderate negative or positive autocorrelation in the factor returns, we allow for zero or positive correlation between the factor and the conditioning variable, and we consider three sample sizes: 24 months, 60 months or 120 months, which covers the relevant range of sample sizes in our empirical analysis (the average sample size in our empirical application is 62 months). We simulate each configuration of parameters $1,000$ times, and report the results in Table 4.

The table shows that the estimation method proposed in Section 2 performs very well in realistic scenarios. In the "base" scenario, we see that with just 60 months of data we are able to reasonably accurately estimate the parameters of this model, including the parameter δ, which allows us to capture daily variation in hedge fund risk exposures. Across a range of different sample sizes, degrees of autocorrelation and correlation, we see that the estimation method performs well: The 90% confidence interval of the distribution of parameter estimates contains the true parameter in all ten scenarios that we consider. This is true even in the last two columns of Table 4, where we consider scenarios that violate our assumption that the innovations to the hedge fund return process are not correlated with leads or lags of the factor or conditioning variable: We consider autocorrelation in both the factor and the conditioning variable, and allow these variables to be correlated. The simulation results indicate that no problem arises in samples of the size that we face in pratice.

Overall, our analysis of daily returns on hedge fund indices and the simulation results of this section provide strong support for the reliability of our estimation procedure in practice. Given daily conditioning variables for hedge fund risk exposures, the results of this section confirm that our method provides a means of obtaining reliable estimates of daily risk exposures from monthly hedge fund returns.

5 Empirical evidence on dynamic risk exposures

Given the relatively short histories of returns for the hedge funds in our sample documented in Table 1, and the data-intensive nature of the models for dynamic risk exposures to be estimated, controlling the number of parameters to be estimated is important. In view of this, we follow Bollen and Whaley (2009) and reduce the full seven-factor Fung-Hsieh model to a more parsimonious two-factor model. For each individual fund, we choose the two-variable subset of factors from the full set of seven that minimizes the Bayesian Information Criterion when the fund's returns are on the left-hand side[14]. Figure 3 shows that the most frequently selected factor is the S&P 500 index, chosen for 65% of the funds. Of the remaining six factors, the most frequently selected is the size factor (SMB) while the second most frequently selected factor is the default spread (BAAMTSY),

[14] As the number of parameters in each of these models is the same, minimizing the BIC is equivalent to maximizing the R^2 or adjusted R^2.

which are chosen for 40% and 35% of funds respectively. Figure 4 breaks this down across the nine strategy groups and shows that the selected second factors are generally consistent with intuition about the factors on which different strategies load. For example, within the Global Macro strategy, the most frequently picked second factor is the return on a portfolio of lookback straddle options on currencies (PTFSFX), whereas for fixed income the default spread (BAAMTSY) is the most frequently picked. With these "optimal" two-factor models for each individual fund, we now turn to models for dynamic exposures to these factors.

5.1 Optimal conditioning variables for dynamic risk exposures

In Section 3.3 we discussed the complete set of 22 variables we consider as conditioning variables for capturing time variations in hedge funds' risk exposures. Although the model described in Section 2.3 extends naturally to handle both more risk factors, f_t, and more conditioning variables, Z_t, the limited time series of data we have on individual funds compels us to keep the model as simple as possible. To that end, we consider only a single conditioning variable in the model. We search across the set of 22 conditioning variables to find the variable that is the most significant for a given fund[15], and to test the significance of the selected conditioning variable we control for the fact that it is the outcome of a specification search by using the "bootstrap reality check" approach of White (2000), described in Section 2.4.2.

Table 5 presents the results of searching for the optimal conditioning variable for each of the 9,538 individual funds. As some of the interaction variables we consider are not available at a daily frequency, the number of parameters in the model can vary from fund to fund. Conditioning variables available at both daily and monthly frequencies are denoted "M,D" in the first column of Table 5, while those available only monthly are denoted "M". Conditioning variables that are labelled "M" generate factor models with five right-hand side variables (the intercept, the two Fung-Hsieh factors selected using the BIC criterion, and two additional right-hand side variables that are interactions between each of the Fung-Hsieh factors and the interaction variable). Conditioning

[15] We measure the significance of a given conditioning variable by the p-value from a joint test that all coefficients on interaction terms involving that variable are zero. The number of parameter restrictions that this implies varies from two to four, depending on whether zero, one or two daily interaction terms are available for inclusion in the model. We use standard errors based on Newey and West (1987) to obtain the Wald test statistic and use the χ^2_p distribution, with $p = 2$, 3, or 4 depending on the number of restrictions being tested, to obtain the p-value. The critical value for the p-value is determined using the reality check of White (2000).

variables labelled "M,D" generate factor models with five, six or seven right-hand side variables: the five regressors from above, plus zero, one or two daily interaction terms $\left(\sum Z_d f_{id}\right)$ depending on whether the 0, 1, or both selected Fung-Hsieh factor are available at the daily frequency, or only monthly (as in the case of the PTFs).

Table 5 presents both the proportions of funds for which a given conditioning variable is selected, and the proportion of funds for which the selected conditioning variable is significant at the 0.10 level, according to the bootstrap reality check testing procedure. Table 5 orders the conditioning variables by the proportion of funds for which it was significant, and the ranking can be seen to be similar when using the selected proportion instead.

Using the bootstrap testing procedure described in Section 2.4, we find that the selected conditioning variable is significant for 2,638 or 28% of funds, at the 0.10 level, substantially more than can be attributed purely to chance. The five most significant (and frequently selected) conditioning variables ΔLevel, the S&P 500 return (and its lag), LIBOR, and VIX. Clearly, funding, performance and sentiment are important drivers of changes in hedge funds' risk exposures. The liquidity variable (Turnover) comes in 6^{th}, which suggests that the role of liquidity in affecting time-variation in funds' exposures is also important. While the frequency of selection is important, it is perhaps more important to consider the increase in the R^2 that obtains from augmenting the factor model with the conditioning variables. Across all conditioning variables, the R^2 rises by a factor of 1.6, from an average of 41.4% for the constant-parameter model to 65% for the model with conditioning information. Adjusted R^2 also increases when we move from the constant-parameter model to the model with conditioning information, from an average of 24.7% to an average of 38.8%. Next, we compare our proposed model with a more sophisticated alternative, the Bollen and Whaley (2009) optimal changepoint model.

5.2 Comparing changepoints with conditioning variables

Table 6 compares the optimal changepoint model employed by Bollen and Whaley (2009) with our model. In the first row we present the proportion of funds for which the changepoint or conditioning variable is significant using the bootstrap approaches described in Section 2.4, which appropriately account for the search process. For comparison purposes for our model, we also present the proportion of funds for which the conditioning variable is significant according to a naïve statistical test that ignores the search across variables. Ferson and Schadt (1996) and Ferson, Simin and Sarkissian (2008) highlight that data-mining is potentially an important concern when using models with conditioning information; and the comparison between the naïve and bootstrap proportions helps to illustrate the extent of the problem.

The first column of Table 6 shows that we detect a significant changepoint for 30.9% of funds using the bootstrap test[16]. Figure 5 shows the most frequently selected changepoint dates between January 1996 and January 2008. The three most frequently selected changepoint dates are January 1996, March 2000, and August 2007. March 2000 corresponds to the peak of the NASDAQ bubble, and July 2007 (the month prior to one of the selected dates) can be linked to the disclosure by Bear Stearns that two of their hedge funds had lost nearly all of their value amid a rapid decline in the market for subprime mortgages. It is hard to link January 1996 to any well-known event in financial markets. Concentrating instead on the dates that are most significant (shaded black in Figure 5) we find that March 2000, April 2001 and August 2008 are the most significant changepoint dates. Again, April 2001 is difficult to link to any well-known event in financial markets. The lack of significant events during several of the frequently selected changepoint months (and the relatively flat nature of the graph of significant break dates) highlights the difficulty in interpreting the results from the changepoint method, a relative advantage of our approach. Turning to the second column of Table 6, we see that our approach based on conditioning information finds 27.7% of funds with a significant conditioning variable (94.6% if we ignore the search process).

The third and fourth columns of the table offer a comparison between the optimal changepoint method and our model. We first take the conditioning variable selected for each fund as given, and then test whether there are any statistically significant changepoints remaining in the intercept and the two Fung-Hsieh factor coefficients. The third column of Table 6 shows that once we choose interaction variables for the fund using our approach, the number of funds for which the changepoint model adds significant explanatory power drops to 15.2%, around one-half of the proportion of funds when the conditioning variable is omitted from the model. This is a substantial reduction, but it also reveals that while our model does capture a large part of the time-variation in factor loadings, there is some significant remaining variation in factor loadings captured by the use of changepoints. This suggests that a hybrid model incorporating both changepoints and conditioning variables may work better than either in isolation. The fourth column of Table 6 shows what happens when we

[16] This figure is based on the *avgF* test statistic; when we bootstrap *supF*, this percentage falls to 28.7%, and bootstrapping *expF* results in 29.8%.

run the experiment in reverse, namely when we first find the optimal changepoint for each fund, and then search across conditioning variables. The numbers show that our method is, if anything, even more useful once a changepoint has been identified: the proportion of funds for which there is a statistically significant conditioning variable rises slightly to 30.1% of the full sample from the 27.7% originally detected.

Table 6 shows the percentage of funds selecting different models, but does not provide information about the magnitude of the improvements offered by our model on a fund-by-fund basis. Figure 6 depicts the performance of the models graphically for the entire set of 9,538 funds in the data, plotting the cumulative distribution functions of the R^2 statistic for all funds for the different models. Confirming Bollen and Whaley's (2009) finding, the figure shows that the changepoint model convincingly beats the constant-parameter model. However, our model based on conditioning variables beats the changepoint model in the sense that the CDF of our model everywhere lies under that of the changepoint model. Finally, the two hybrid models considered in columns three and four of Table 6 both beat our model, confirming that there are gains to combining the changepoint and conditioning variable approaches. Table 7 reproduces some of the percentiles plotted in Figure 6, and shows that the dominance of the interaction approach is also observed when we compare adjusted R^2 statistics, and not just raw R^2s.

5.3 The value of daily conditioning information

Figure 7 analyzes one source of the improvements offered by our model. As in Figure 6, we plot the CDF of the R^2s from the constant-parameter and interaction-based models. We then make one addition to the figure, namely, we include the CDF of R^2s from model that includes only monthly (not daily) conditioning information. The figure shows that if we only consider monthly conditioning information, our model does approximately as well as the optimal changepoint model; slightly worse on low R^2 funds, and slightly better on high R^2 funds. Clearly, the major improvement in the model based on conditioning information relative to the optimal changepoint model comes from the use of daily conditioning information. Table 7 confirms that this is true even when we account for the reduction in the number of variables employed in the monthly model: Comparing across the third and sixth columns of the table in the adjusted R^2 panel, it is clear that the model with added daily interactions dominates the model with only monthly interactions at all percentiles.

The test results in Table 6 support this finding: when restricting conditioning information to monthly variables, we find 17.7% of funds with statistically significant variations in factor exposures. When we also consider daily information, the proportion increases to 27.7%. For just 1.3% of funds do we find significant variation using monthly information but not when using both daily and monthly information, while for 11.3% of funds we find significant variation when using daily conditioning information, but no significant variation when only using monthly conditioning information. Stated differently, for a total of 1076 funds we find evidence of varying risk exposures using daily information where no evidence could be found when using only monthly information. We thus conclude that accounting for the high frequencies at which hedge funds alter their risk exposures is very important when modeling their systematic risk exposures.

As an aside, Table 7 also presents one further change in our model, which follows Christophersen, Ferson and Glassman (1998). The change is to augment the interaction model to allow for time-varying alpha, i.e., interacting the intercept with the conditioning information variable in addition to the time-varying regressors. This addition further increases the explanatory power provided by our approach – the final column of Table 7 shows that this improvement is quite substantial.

5.4 Conditioning variables across hedge fund styles

We now turn to economic interpretations of some of the results from the models with conditioning information. Table 8 lists the top three most often selected interaction variables across the nine strategy groups. The first column of the table lists the percentage of funds within each strategy group that have statistically significant interaction variables once the process of searching across the 22 interaction variables is accounted for. The most frequently selected variables across all strategies are ΔLevel, the S&P 500 return and VIX. In terms of the four categories, namely liquidity, funding and leverage, sentiment and performance, variations in funding costs appear to be the main driver of the changes in factor loadings across all strategy groups (accounting for 10 of the 27 top three variables per strategy). This is perhaps unsurprising considering the significant role of leverage in hedge funds' return-generation strategies. Studies of the effect of leverage on hedge fund returns have been somewhat sparse given the lack of detailed data on this aspect of hedge funds' activities, and authors have adopted different strategies for ascertaining these effects. For example, using simulations, Lo and Khandani (2008) highlight that systematic portfolio deleveraging by long-short equity hedge funds could have been responsible for the "quant meltdown" of August 2007. Liang (1999) uses the self-reported data in the HFR database on hedge funds' use of leverage, and documents that while there is no discernible difference across all funds between those using leverage and those not using leverage, convertible arbitrage and merger arbitrage funds benefit from the use of leverage, while emerging market funds are hurt by the use of leverage. In keeping with this observation, Table 8 shows that both Relative Value (which contains merger arbitrage funds) and Fixed Income (which contains convertible arbitrage funds) select ΔLevel and LIBOR as two of their most frequently picked interaction variables.

6 Conclusion

Recent research on hedge funds and mutual funds has documented the importance of accounting for the dynamic nature of the risk exposures of these actively managed investment vehicles. Several approaches have been proposed in the literature, including modelling these risk exposures as unobserved latent factors, and employing optimal changepoint regression techniques. We add to this literature with a new model that is related to the well-known Ferson and Schadt (1996) conditional performance evaluation model, extending this approach to capture the daily variation in hedge funds' factor exposures through the use of daily conditioning variables.

Using a comprehensive data base of hedge funds over the 1995 to 2008 period, we find that our model performs well on statistical grounds, beating the constant parameter model, and also outperforming more sophisticated models such as the changepoint regression approach. The extension of our model to capture daily variation in factor exposures is important in this context: A model with purely monthly interaction variables only performs approximately as well as the changepoint regression approach. In addition to its good statistical performance, our approach provides the added benefit of economic interpretability of the changes in factor exposures: We find that variations in the cost of leverage, liquidity, movements in the VIX, and the performance of commonly employed benchmarks such as the S&P 500 are important drivers of hedge funds' risk exposures. These findings add to the heretofore sparse evidence on the role of leverage and liquidity in hedge funds' risk profiles, an area of increasing importance in light of recent public debates.

Appendix

The consolidated hedge fund database

The final combined database used in this paper comprises 9,538 live and dead funds of funds and hedge funds for which contiguous returns data for at least 24 months are available over the interval spanning 1995 to 2008. This appendix describes how this combined database was created.

The hedge fund and fund of funds data span three different sources: TASS, HFR, and CISDM, the time-stamp on the databases is December 2008. There are a total of 17,732 live and dead funds across all the databases, for which both administrative information (including fund characteristics) and returns information were available. This number is misleading, since an individual fund can appear multiple times from different vendors, resulting in duplication. The information available in the administrative files of the databases are used to systematically remove duplicates. The criteria used for elimination are:

1. Key name: different funds from different database sources occasionally name the same fund differently. A "Key name" is created for each unique fund using a name-matching algorithm that eliminates differences on account of hyphenation, misspellings and punctuation.

2. Currency: funds that have the same Key names might offer shares to investors in multiple different currencies. If the returns are the same when converted into a common currency, the funds are considered duplicates, otherwise they are preserved as different funds.

3. Strategy: there are 78 different strategies listed in the consolidated administrative information file coming from the four different database sources. Using the classification system employed in Naik, Ramadorai and Stromqvist (2007), these 78 strategies are condensed into nine broad categories. The correspondence between the strategies encountered in the administrative file, and the broad categories is presented in the Table A.1. below.

4. Management Company: since the information came from three different sources, the names of the management companies of funds are also occasionally differently spelled. The names of management companies are standardized in the same way as the creation of key names (point 1. above).

5. Length of History: the administrative files include information such as from- and to-dates, which provide the start and end date of when information about the hedge fund or fund-of-funds was recorded in the database source. If there are two or more funds that are completely identical

in terms of key name, currency, strategy, and management company, the fund for which the longest period of information is available is selected.

Once this process is completed, additional criteria from the administrative files are used to remove any remaining duplicates. Funds with identical key names, currencies, and from-dates are compared based on their reported minimum investment, redemption notice periods and lock-up periods. If, within these subgroups, all of the three administrative fields are the same, the funds are assumed to be the same. In cases of duplicates, those with the greatest length of history are chosen, as before. This procedure leaves us with information on $12,560$ unique hedge funds and funds-of-funds. We then impose the additional requirement that the funds have at least 24 months of contiguous returns information available. This eliminates a total of $3,022$ funds, leaving a total of $9,538$ funds in the final data. The sources of these funds and the percentage that are alive and defunct (either liquidated or closed to new investments) are shown in Table A.2.

Table A.1.
Vendor Provided Strategies and Mapped Strategies

This table shows the fund strategies provided by HFR, TASS and CISDM data vendors in the first column, and the nine strategies to which these are mapped in the second column.

Strategy in Consolidated Database	Mapped Strategy
Arbitrage	Relative Value
Capital Structure Arbitrage	Relative Value
Convertible Arbitrage	Fixed Income
CPO-Multi Strategy	Other
CTA – Commodities	Other
CTA-Systematic/Trend-Following	Other
Dedicated Short Bias	Directional Traders
Directional Traders	Directional Traders
Discretionary Trading	Other
Distressed Securities	Multi-Process
Emerging	Emerging
Emerging Markets	Emerging
Emerging Markets: Asia	Emerging
Emerging Markets: E. Europe/CIS	Emerging
Emerging Markets: Global	Emerging
Emerging Markets: Latin America	Emerging
Equity Hedge	Security Selection
Equity Long Only	Directional Traders
Equity Long/Short	Security Selection
Equity Market Neutral	Security Selection
Equity Non-Hedge	Directional Traders
Event Driven	Multi-Process
Event Driven Multi Strategy	Multi-Process
Event-Driven	Multi-Process
Fixed Income	Fixed Income
Fixed Income – MBS	Fixed Income
Fixed Income Arbitrage	Fixed Income
Fixed Income: Arbitrage	Fixed Income
Fixed Income: Convertible Bonds	Fixed Income
Fixed Income: Diversified	Fixed Income
Fixed Income: High Yield	Fixed Income
Fixed Income: Mortgage-Backed	Fixed Income
FOF-Conservative	Funds of Funds
FOF-Invest Funds in Parent Company	Funds of Funds
FOF-Market Neutral	Funds of Funds
FOF-Multi Strategy	Funds of Funds
FOF-Opportunistic	Funds of Funds
FOF-Single Strategy	Funds of Funds
Foreign Exchange	Global Macro
Fund of Funds	Funds of Funds
Global Macro	Global Macro
HFRI	Other
Index	Other
Long Bias	Directional Traders

Table A.1. (Continued)

Strategy in Consolidated Database	Mapped Strategy
Long/Short Equity Hedge	Security Selection
Long-Short Credit	Fixed Income
Macro	Global Macro
Managed Futures	Other
Market Timing	Directional Traders
Merger Arbitrage	Relative Value
Multi Strategy	Multi-Process
Multi-Process	Multi-Process
Multi-Strategy	Multi-Process
No Bias	Relative Value
Option Arbitrage	Relative Value
Other Relative Value	Relative Value
Private Placements	Multi-Process
Regulation D	Relative Value
Relative Value	Relative Value
Relative Value Arbitrage	Relative Value
Relative Value Multi Strategy	Multi-Process
Sector	Directional Traders
Sector: Energy	Directional Traders
Sector: Financial	Directional Traders
Sector: Health Care/Biotechnology	Directional Traders
Sector: Miscellaneous	Directional Traders
Sector: Real Estate	Directional Traders
Sector: Technology	Directional Traders
Security Selection	Security Selection
Short Bias	Directional Traders
Short Selling	Directional Traders
Statistical Arbitrage	Relative Value
Strategy	Other
Systematic Trading	Directional Traders
Tactical Allocation	Directional Traders
UNKNOWN STRATEGY	Other
Variable Bias	Directional Traders
(blank)	Other

Table A.2.
Data Sources

This table shows the number of funds from each of the three sources (HFR, TASS and CISDM), and the number of these funds that are alive and defunct (either liquidated or closed) in the consolidated universe of hedge fund data.

Source Dataset	Number of Funds	Alive	Defunct	% Defunct
TASS	3397	1813	1584	46.629%
HFR	3537	2120	1417	40.062%
CISDM	2604	1265	1339	51.421%
Total	9538	5198	4340	45.502%

References

[1] Ackermann, C., R. McEnally, and D. Ravenscraft, 1999, The Performance of hedge funds: Risk, return and incentives, Journal of Finance 54, 833-874.

[2] Admati, A., S. Bhattacharya, P. Pfleiderer; and S. Ross, 1986, On Timing and Selectivity. Journal of Finance, 715-732.

[3] Agarwal, V., N. Daniel and N. Y. Naik, 2009, Role of managerial incentives and discretion in hedge fund performance, Journal of Finance, forthcoming.

[4] Agarwal, V., W. Fung, Y. Loon and N. Y. Naik, 2009, Risk and Return in Convertible Arbitrage: Evidence from the Convertible Bond Market, Unpublished working paper.

[5] Andrews, D.W.K., I. Lee and W. Ploberger, 1996, Optimal Changepoint Tests for Normal Linear Regression, Journal of Econometrics, 70, 9-38.

[6] Aragon, G., 2005, Share restrictions and asset pricing: Evidence from the hedge fund industry, Journal of Financial Economics 83, 33-58.

[7] Bollen, N.P.B. and J.A. Busse, 2001, On the Timing Ability of Mutual Fund Managers, Journal of Finance, 56, 1075-1094.

[8] Bollen, N.P.B., and R.E. Whaley, 2009, Hedge Fund Risk Dynamics: Implications for Performance Appraisal, Journal of Finance, forthcoming.

[9] Brunnermeier, M., and S. Nagel, 2004, Hedge Funds and the Technology Bubble, Journal of Finance, 59(5), 2013-2040.

[10] Busse, J., 1999, Volatility Timing in Mutual Funds: Evidence from Daily Returns, Review of Financial Studies 12, 1009-1041.

[11] Cao, C., Y. Chen and B. Liang, 2009, Can Hedge Funds Time Market Liquidity?, working paper, University of Massachusetts at Amherst.

[12] Chance, D., and M. Hemler, 2001, The Performance of Professional Market Timers: Daily Evidence from Executed Strategies, Journal of Financial Economics, 62, 377–411.

[13] Chen, H.-L., N. Jegadeesh, and R. Wermers, 2000, The value of active mutual fund management: An examination of the stockholdings and trades of fund managers, Journal of Financial and Quantitative Analysis, 35, 343-368.

[14] Chen, Y. and B. Liang, 2007, Do Market Timing Hedge Funds Time the Markets?, Journal of Financial and Quantitative Analysis, 42, 827-856.

[15] Chen, Z., and P. Knez, 1996, Portfolio Performance Measurement: Theory and Applications. Review of Financial Studies, 9, 511-555.

[16] Christopherson, J.A., W. Ferson and D. Glassman, 1998, Conditioning Manager Alpha on Economic Information: Another Look at the Persistence of Performance, Review of Financial Studies, 11, 111-142.

[17] Da, Z., P. Gao and R. Jagannathan, 2009, When Does A Mutual Fund's Trade Reveal Its Skill? working paper, Northwestern University.

[18] Daniel, K., Grinblatt, M., Titman, S., Wermers, R., 1997, Measuring mutual fund performance with characteristic-based benchmarks. Journal of Finance 52, 1035–1058.

[19] Distaso, W., M. Fernandes and F. Zikes, 2009, Tailing Tail Risk in the Hedge Fund Industry, working paper, Imperial College London.

[20] Ferson, W.E., T. Henry and D. Kisgen, 2006, Evaluating Government Bond Fund Performance with Stochastic Discount Factors, Review of Financial Studies 19, 423-456.

[21] Ferson, W.E., and K. Khang, 2002, Conditional Performance Measurement Using Portfolio Weights: Evidence for Pension Funds, Journal of Financial Economics 65, 249-282.

[22] Ferson, W.E., S. Sarkissian and T. Simin, 2008, Asset Pricing Models with Conditional Alphas and Betas: The Effects of Data Snooping and Spurious Regression, Journal of Financial and Quantitative Analysis 43, 331-354.

[23] Ferson, W.E. and R.W. Schadt, 1996, Measuring Fund Strategy and Performance in Changing Economic Conditions, Journal of Finance, 51, 425-461.

[24] Fung, W., and D.A. Hsieh, 1997, Empirical characteristics of dynamic trading strategies: the case of hedge funds, Review of Financial Studies 10, 275-302.

[25] Fung, W., and D.A. Hsieh, 2001, The risk in hedge fund strategies: theory and evidence from trend followers, Review of Financial Studies 14, 313-341.

[26] Fung, W., and D.A. Hsieh, 2004a, Hedge fund benchmarks: A risk based approach, Financial Analysts Journal 60, 65-80.

[27] Fung, W., and D.A. Hsieh, 2004b, Asset-Based Style Factors for Hedge Funds, Financial Analysts Journal, 60, 65-80.

[28] Getmansky, M., 2004, The Life Cycle of Hedge Funds: Fund Flows, Size and Performance, Unpublished working paper.

[29] Getmansky, M.., A.W. Lo, and I. Makarov, 2004, An econometric model of serial correlation and illiquidity in hedge fund returns, Journal of Financial Economics 74, 529-610.

[30] Goetzmann W.N., Ingersoll J.E., and Z. Ivkovic, 2000, Monthly Measurement of Daily Timers, Journal of Financial and Quantitative Analysis, 35(3) pp.257-290.

[31] Goetzmann W.N., Ingersoll J.E., and Ross S.A., 2003, High-Water Marks and Hedge Fund Management Contracts, Journal of Finance, 58(4), 1685-1718.

[32] Graham, J., Harvey, C., 1996, Market timing ability and volatility implied in investment newsletters' asset allocation recommendations. Journal of Financial Economics 42, 397–422.

[33] Griffin, J., F. Nardari and R. Stulz, 2007, Do investors trade more when stocks have performed well? Evidence from 46 countries, Review of Financial Studies, 20, 905–951.

[34] Hasbrouck, J., 2009, Trading Costs and Returns for US Equities: Estimating Effective Costs from Daily Data, Journal of Finance, forthcoming.

[35] Henriksson, R., and R. Merton, 1981, On Market Timing and Investment Performance. II. Statistical procedures for Evaluating Forecasting Skills. Journal of Business, 54, 513-533.

[36] Jagannathan, R., and R. Korajczyk, 1986, Assessing the Market Timing Performance of Managed Portfolios. Journal of Business, 59, 217-235.

[37] Jagannathan, R., A. Malakhov and D. Novikov, 2009, Do hot hands exist among hedge fund managers? An empirical evaluation, Journal of Finance, forthcoming.

[38] Jagannathan, R., and Z. Wang, 1996, The Conditional CAPM and the Cross-Section of Expected Returns, Journal of Finance, 51, 3-54.

[39] Kacperczyk, M., C. Sialm and L. Zheng, 2007, Unobserved Actions of Mutual Funds, Review of Financial Studies, 21, 2379-2416.

[40] Khandani, A., and A. Lo, 2008, What Happened to the Quants in August 2007: Evidence from Factors and Transactions Data, Unpublished Working Paper.

[41] Kosowski, R., N.Y. Naik and M. Teo, 2007, Do hedge funds deliver alpha? A Bayesian and bootstrap analysis, Journal of Financial Economics, 84, 229-264.

[42] Lehmann, B., and D. Modest, 1987, Mutual Fund Performance Evaluation: A Comparison of Benchmarks and Benchmark Comparisons. Journal of Finance, 42, 233-265.

[43] Lemmon, M. and E. Portniaguina, 2006, Consumer confidence and asset prices: Some empirical evidence, Review of Financial Studies, 19, 1499–1529.

[44] Liang, B., 1999, On the Performance of Hedge Funds, Financial Analysts Journal, Summer edition, 72-85.

[45] Liang, B., and Y. Chen, 2007, Do Market Timing Hedge Funds Time the Markets? Journal of Financial and Quantitative Analysis 42, 827-856.

[46] Mamaysky, H., M. Spiegel and H. Zhang, 2008, Estimating the Dynamics of Mutual Fund Alphas and Betas, Review of Financial Studies, 21, 233-264.

[47] Naik, N.Y., T. Ramadorai and M. Stromqvist, Capacity constraints and hedge fund strategy returns, 2007, European Financial Management, 13, 239-256.

[48] Newey, W.K., and K.D. West, 1987, A Simple, Positive Semidefinite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix, Econometrica, 55, 703-708.

[49] Panageas, S. and M. Westerfield, 2009, High-Water Marks: High Risk Appetites? Convex Compensation, Long Horizons, and Portfolio Choice, Journal of Finance, 64(1), 1-36.

[50] Patton, A., 2009, Are "Market Neutral" Hedge Funds Really Market Neutral?, Review of Financial Studies, 22(7), 2495-2530.

[51] Pollet, J., and M.I. Wilson, 2008, How Does Size Affect Mutual Fund Behavior? Journal of Finance, 63(6), 2941-2969.

[52] Politis, D.N., and J.P. Romano, 1994, The Stationary Bootstrap, Journal of the American Statistical Association, 89, 1303-1313.

[53] Qiu, L., and I. Welch, 2006, Investor sentiment measures, Unpublished working paper.

[54] Ramadorai, T., 2009, The Secondary Market for Hedge Funds and the Closed-Hedge Fund Premium, Unpublished working paper.

[55] Rubin, R., A. Greenspan, J.A. Levitt and B. Born, 1999, Hedge Funds, Leverage, and the Lessons of Long-Term Capital Management, Report of the President's Working Group on Financial Markets

[56] Sadka, R., 2009, Liquidity Risk and the Cross-Section of Expected Hedge Fund Returns, Unpublished working paper.

[57] Sullivan, R., A. Timmermann and H. White, 1999, Data-Snooping, Technical Trading Rule Performance, and the Bootstrap, Journal of Finance, 54, 1647-1692.

[58] Teo, M., 2009, Geography of Hedge Funds, Review of Financial Studies, forthcoming.

[59] Teo, M., 2009, Hedge fund capacity constraints, liquidity, and hierarchy costs, Unpublished working paper.

[60] Treynor, J., and K. Mazuy, 1966, Can Mutual Funds Outguess the Market? Harvard Business Review, 44, 131-136.

[61] Whaley, R.E., 2000, The investor fear gauge, Journal of Portfolio Management 26, 12-17.

[62] White, H., 2000, A Reality Check for Data Snooping, Econometrica, 68, 1097-1126.

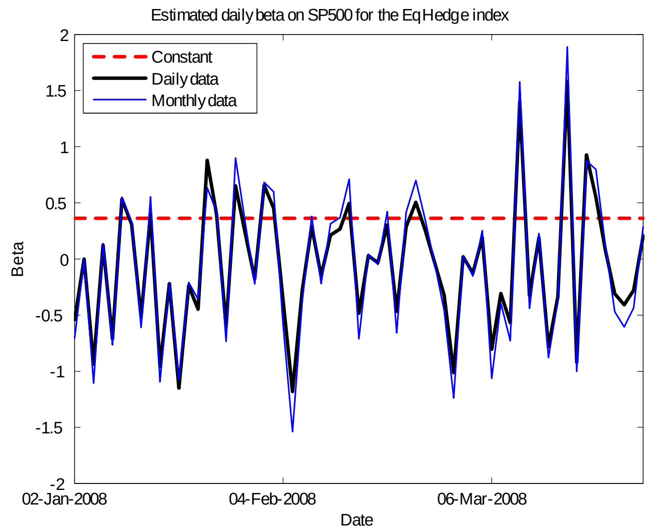

Figure 1: *Estimates of the daily exposure of the HFR equity hedge index to the SP500 index over the first quarter of 2008 from three models: constant beta, time-varying beta using daily returns on the index, and time-varying beta using the proposed method based only on monthly returns.*

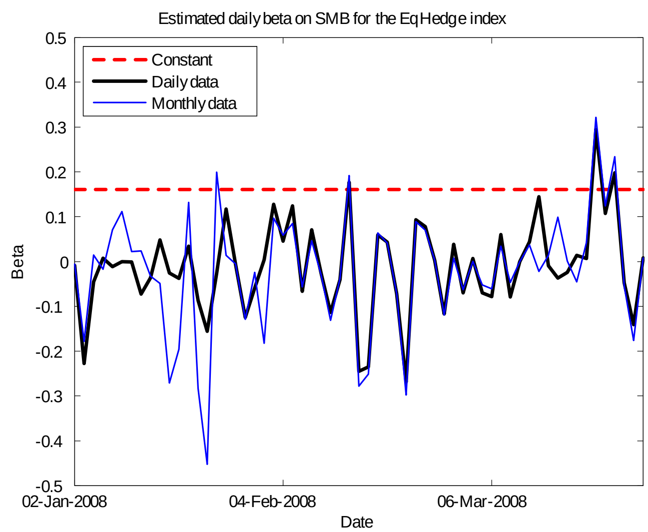

Figure 2: *Estimates of the daily exposure of the HFR equity hedge index to the SMB index over the first quarter of 2008 from three models: constant beta, time-varying beta using daily returns on the index, and time-varying beta using the proposed method based only on monthly returns.*

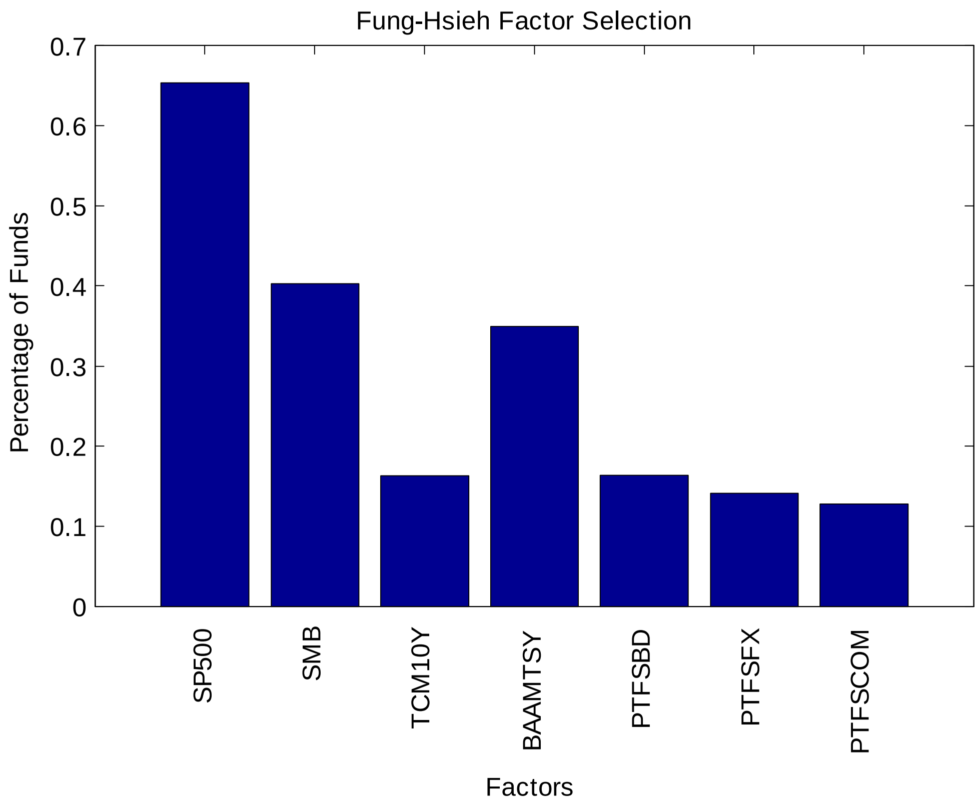

Figure 3: *Proportion of times each of the Fung-Hsieh (2004) factors are selected in a two-factor model, as a percentage of the 9538 individual funds.*

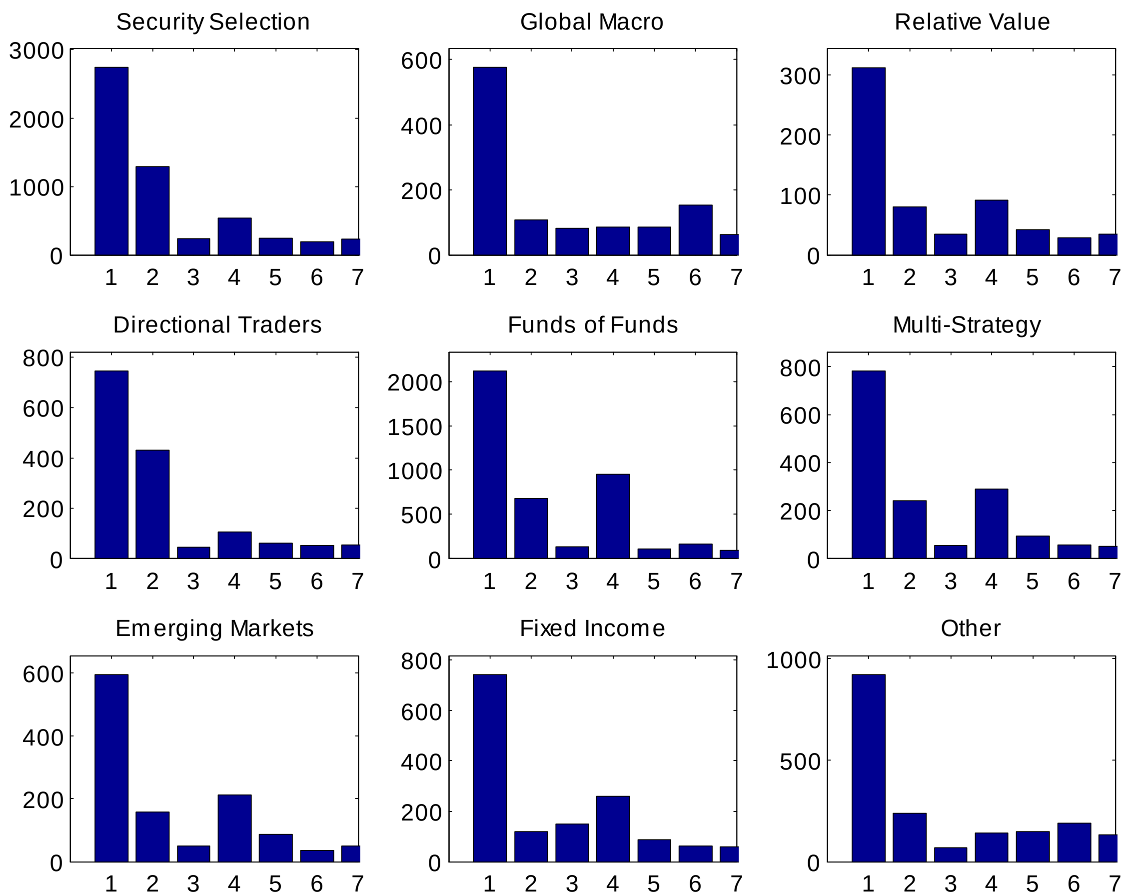

Figure 4: *Number of times each of the Fung-Hsieh (2004) factors are selected in a two-factor model, for each of the nine hedge fund strategies. Factors 1–7 are, in order, SP500, SMB, TCM10Y, BAAMTSY, PTFSBD, PTFSFX, PTFSCOM.*

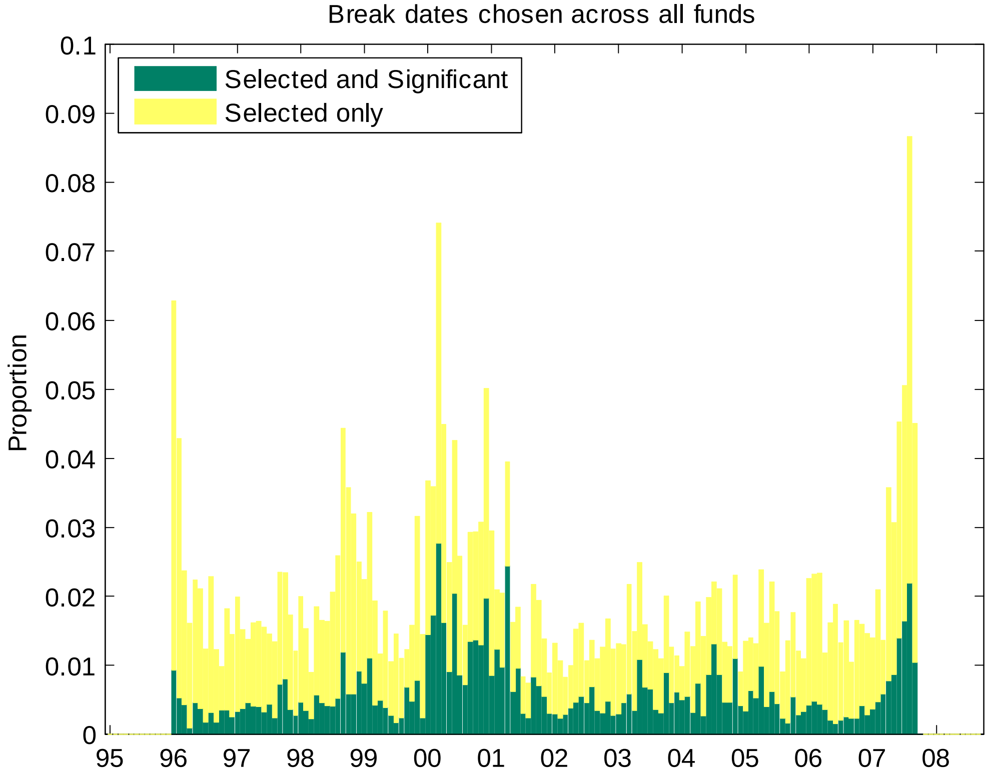

Figure 5: *Most frequently selected changepoint dates, as a percentage of the available funds at each date.*

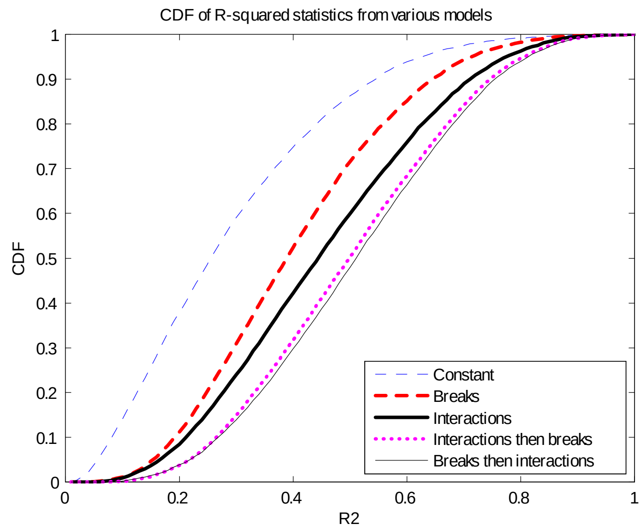

Figure 6: *Empirical cumulative distribution function (CDF) of* R^2 *statistics from the constant-parameter model, optimal changepoint (or "break") model, model with conditioning information ("interactions") or combinations of both models, across 9538 individual funds.*

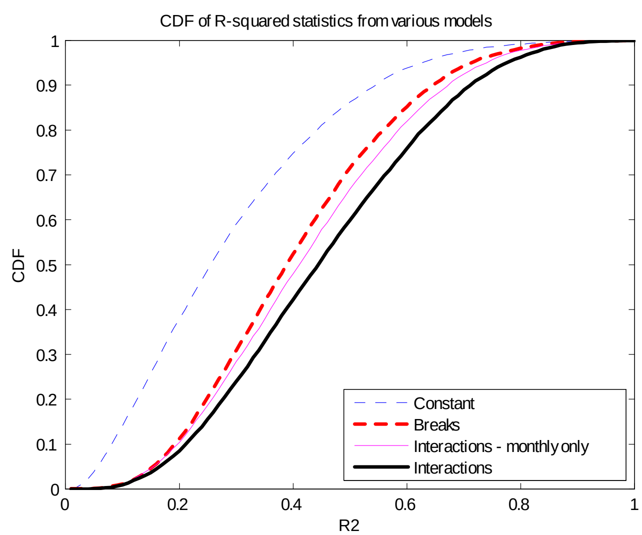

Figure 7: *Empirical cumulative distribution function (CDF) of* R^2 *statistics from the constant-parameter model, a model with breaks, a model with monthly conditioning information only, and a model with both daily and monthly conditioning information, across 9538 individual funds.*

Table 1
Summary Statistics

This table shows summary statistics for the funds in our sample. Panel A reports the percentiles of the pooled (cross-sectional) distribution of returns, unsmoothed returns, AUM, management fees, incentive fees, lockup and redemption notice periods. Panel B shows the percentages of funds in the consolidated sample of 9,538 which have return histories of the lengths specified in the column headers. Panel C shows the percentages of the 9,538 funds in each of the strategies represented in the rows.

Panel A

	Returns	Unsmoothed Returns	AUM ($MM)	Management Fee	Incentive Fee Fee	Lockup (Months)	Redemption Notice (Months)
25th Prctile	-0.700	-0.841	9.400	1.000	15.000	0.000	0.333
50th Prctile	0.720	0.710	32.000	1.500	20.000	0.000	1.000
75th Prctile	2.230	2.363	106.756	2.000	20.000	6.000	1.500
Mean	0.845	0.847	166.714	1.400	16.635	3.438	1.125

Panel B

	<36 Months	>=36 , <60	>=60
Length(Return History)	17.100	31.233	51.667

Panel C

	Percent of Funds in Strategy
Security Selection	28.727
Global Macro	6.039
Relative Value	3.271
Directional Traders	7.811
Funds of Funds	22.248
Multi-Process	8.209
Emerging Markets	6.238
Fixed Income	7.779
CTAs and Others	9.677

Table 2

Factor models for daily and monthly hedge fund style index returns

Table 2 shows results from a simple two-factor model applied to five hedge fund style index returns, identified in the first row of the table. In all cases a constant is included, and two factors from the set of four daily Fung-Hsieh factors are selected using the Bayesian Information Criterion. Robust t-statistics are reported below the parameter estimates, and the R2 and adjusted R2 are reported in the bottom two rows of the table.

	Equity Hedge		Event Driven		Convertible Arb		Merger Arb		Market Neutral	
	Daily	Monthly	Daily	Monthly	Daily	Monthly	Daily	Monthly	Daily	Monthly
Constant	-0.005	-0.007	0.012	0.008	-0.034	-0.021	0.016	0.015	0.004	0.004
t-stat	-0.580	-0.865	1.654	1.498	-1.775	-1.239	2.869	2.620	0.621	0.632
SP500	0.362	0.536	0.256	0.426	-0.105	0.249	0.140	0.151		
t-stat	16.252	6.641	12.714	11.280	-3.025	2.399	5.118	3.549		
SMB	0.161	0.140							-0.019	0.000
t-stat	2.979	2.039							-0.828	-0.004
TCM10Y									-0.139	-0.038
t-stat									-1.072	-0.057
BAAMTSY			-1.807	-1.279	-5.950	-15.478	-0.245	-0.197		
t-stat			-2.512	-2.269	-2.457	-3.530	-0.354	-0.318		
R2	0.681	0.695	0.578	0.729	0.210	0.703	0.458	0.335	0.157	0.000
R2adj	0.681	0.685	0.577	0.721	0.209	0.694	0.457	0.314	0.156	-0.031

Table 3

Factor models for daily and monthly hedge fund style index returns, with time-varying betas

Table 3 shows results from a two-factor model applied to five hedge fund style index returns, identified in the first row of the table, allowing for time variation in the factor exposures through conditioning variables. This model is described in equations (8) and (9). Two factors from the set of four daily Fung-Hsieh factors are selected using the Bayesian Information Criterion, and are identified in Table 2. Robust t-statistics are reported below the parameter estimates, and the R2 and adjusted R2 are also reported. The fourth-last row presents the bootstrap p-value for the joint significance of the coefficients on the interaction terms (gamma1, gamm2, delta1, delta2), controlling for the search across possible interaction variables that was conducted. The third-last row presents the naive p-value from a similar test that ignores the search process. The second- and third-last rows present the correlation between the time series of daily factor exposures estimated using daily and monthly data, for each of the two factors. The selected conditioning variable is presented in the final row.

	Equity Hedge		Event Driven		Convertible Arb		Merger Arb		Market Neutral	
	Daily	Monthly	Daily	Monthly	Daily	Monthly	Daily	Monthly	Daily	Monthly
Alpha	0.001	-0.001	0.010	0.000	-0.015	0.019	0.014	0.014	0.003	0.007
t-stat	0.097	-0.152	1.437	0.028	-0.854	2.187	2.578	2.312	0.485	1.523
Beta1	0.337	0.443	0.262	0.441	-0.073	0.237	0.119	0.170	-0.013	-0.006
t-stat	15.518	9.011	16.528	12.887	-2.670	3.273	6.853	3.296	-0.612	-0.162
Beta2	0.237	0.187	-1.683	-0.734	-2.409	2.089	-0.782	-0.428	-0.239	0.897
t-stat	7.124	3.107	-3.228	-1.062	-2.974	1.138	-2.318	-0.417	-1.913	2.395
Gamma1	-5.411	-6.998	-0.023	-0.053	-0.730	-2.550	-0.056	-0.175	-0.360	-0.838
t-stat	-3.453	-1.537	-0.519	-0.248	-1.070	-1.317	-0.931	-1.447	-1.395	-2.849
Gamma2	2.758	4.520	-0.768	-0.398	58.606	125.310	-2.469	-3.353	-0.465	-4.926
t-stat	1.519	1.075	-0.608	-0.179	2.959	2.857	-2.518	-1.224	-0.632	-1.916
Delta1	6.657	-36.442	-0.385	0.363	0.066	0.270	-0.237	0.056	0.292	0.829
t-stat	0.694	-2.090	-4.805	1.142	3.313	12.730	-2.481	0.539	1.294	2.971
Delta2	-90.453	-174.020	-7.598	-21.166	1.532	0.528	7.428	1.787	0.624	6.944
t-stat	-7.497	-5.217	-6.067	-5.172	6.182	0.261	2.411	0.153	0.890	2.671
R2	0.720	0.790	0.603	0.813	0.306	0.930	0.520	0.373	0.183	0.289
R2adj	0.719	0.769	0.601	0.794	0.303	0.924	0.518	0.310	0.180	0.218
Boot p-val	0.000	0.006	0.000	0.003	0.000	0.000	0.000	0.305	0.639	0.255
Naïve p-val	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.009	0.000	0.000
Corr-b1[t]	0.983		0.918		0.642		0.946		0.609	
Corr-b2[t]	0.849		0.842		0.798		0.762		0.249	
Interact var	Turnover		ΔSlope		SP500 lag1		Lagged ΔLevel		LIBOR	

Table 4
Results from a simulation study of the estimation method

Table 4 reports the mean and standard deviation, across 1000 independent simulation replications, of estimates of the parameters of a model of time-varying factor exposures. The results for ten different simulation designs are presented. Simulation design parameters are presented in the first panel of the table, and the mean and standard deviation of the simulation distribution of parameter estimates are presented in the second and third panels. The true values of the four parameters are presented in the first column of the table. The values for alpha, gamma and delta are scaled up by a factor of 100 for ease of interpretability.

			1	2	3	4	5	6	7	8	9	10
		True values	Base scenario	Short sample	Long sample	Low autocorr in Z	High autocorr in Z	Corr b/w F, Z	Neg autocorr in F, rhoFZ=0	Pos autocorr in F, rhoFZ=0	Neg autocorr in F, rhoFZ=0.5	Pos autocorr in F, rhoFZ=0.5
	T		60	24	120	60	60	60	60	60	60	60
	rhoFZ		0.0	0.0	0.0	0.0	0.0	0.5	0.0	0.0	0.5	0.5
	phiZ		0.5	0.5	0.5	0.0	0.9	0.5	0.5	0.5	0.5	0.5
	phiF		0.0	0.0	0.0	0.0	0.0	0.0	-0.2	0.2	-0.2	0.2
Mean	Alpha*100	0.758	0.715	0.827	0.794	0.729	0.773	0.812	0.780	0.735	0.725	0.721
Mean	Beta	0.400	0.400	0.397	0.399	0.400	0.401	0.400	0.401	0.400	0.399	0.401
Mean	Gamma*100	0.200	0.198	0.198	0.200	0.198	0.200	0.200	0.199	0.201	0.198	0.199
Mean	Delta*100	-0.400	-0.391	-0.400	-0.409	-0.399	-0.404	-0.410	-0.381	-0.392	-0.397	-0.394
St dev	Alpha*100		0.089	0.146	0.062	0.089	0.092	0.194	0.085	0.091	0.191	0.191
St dev	Beta		0.035	0.060	0.024	0.033	0.035	0.035	0.042	0.031	0.041	0.029
St dev	Gamma*100		0.005	0.009	0.003	0.008	0.003	0.005	0.006	0.004	0.005	0.004
St dev	Delta*100		0.038	0.062	0.026	0.035	0.052	0.034	0.039	0.034	0.037	0.031

Table 5
Selection of Conditioning Variables

Table 2 shows results from the interaction-based model applied to the 9,538 funds in the data. In order, the columns report if the conditioning variable has only monthly (M) or monthly and daily (M,D) data; the variable name; the number of funds for which the conditioning variable is selected (the funds for which the variable beats all the other conditioning variables on the R^2 criterion); the mean R^2 from the benchmark constant-parameter factor model; the mean R^2 from the factor model augmented with the selected conditioning variable; the ratio of the two R^2's; the number of funds for which the conditioning variable is significant using the bootstrap reality check; the average R^2 from the benchmark and conditional factor models (and their ratio) only for those funds for which the conditioning variable is significant

			Funds for which variable is *selected*				Funds for which variable is *significant*			
	Frequency	Variable	Number	Base R2	Best R2	Best/Base	Number	Base R2	Best R2	Best/Base
1	M, D	ΔLevel	783	0.293	0.488	1.666	312	0.374	0.636	1.698
2	M, D	S&P500 Return	771	0.325	0.495	1.520	275	0.439	0.668	1.521
3	M, D	LIBOR	571	0.306	0.476	1.557	205	0.429	0.639	1.491
4	M, D	Lagged S&P500 Return	469	0.316	0.491	1.555	173	0.441	0.677	1.534
5	M, D	VIX	490	0.285	0.474	1.662	160	0.386	0.666	1.723
6	M, D	Turnover	444	0.311	0.490	1.574	158	0.418	0.672	1.606
7	M, D	Lagged LIBOR	422	0.325	0.490	1.509	151	0.467	0.672	1.438
8	M, D	Lagged Turnover	467	0.278	0.446	1.604	133	0.386	0.634	1.646
9	M	Michigan Sentiment index	394	0.294	0.445	1.515	113	0.431	0.638	1.479
10	M, D	Lagged ΔLevel	413	0.280	0.450	1.610	101	0.425	0.677	1.590
11	M, D	Default Spread	353	0.284	0.447	1.573	90	0.418	0.654	1.565
12	M	CD 1 month	310	0.309	0.453	1.467	87	0.459	0.643	1.401
13	M	Fund performance (3 months)	487	0.247	0.391	1.584	87	0.419	0.632	1.509
14	M, D	Lagged Default Spread	377	0.296	0.460	1.556	86	0.412	0.663	1.611
15	M, D	ΔCurvature	384	0.272	0.439	1.613	85	0.418	0.682	1.633
16	M, D	Lagged VIX	358	0.266	0.438	1.642	81	0.366	0.627	1.712
17	M	Fund performance (1 month)	601	0.240	0.384	1.603	78	0.341	0.595	1.746
18	M	Lagged Michigan index	373	0.282	0.430	1.527	75	0.435	0.634	1.458
19	M, D	ΔSlope	325	0.269	0.426	1.583	62	0.404	0.660	1.635
20	M	Lagged CD 1 month	226	0.292	0.433	1.481	47	0.429	0.618	1.440
21	M, D	Lagged ΔCurvature	273	0.262	0.416	1.586	42	0.426	0.678	1.591
22	M, D	Lagged ΔSlope	247	0.274	0.443	1.618	37	0.385	0.645	1.673
Total		Total/Average	9538	0.287	0.450	1.573	2638	0.414	0.650	1.577

Table 6
Comparing Changepoints With Conditioning Variables

This table shows results from a comparison between the change-point model of Bollen and Whaley (2009) and the conditioning variables (or "interactions") method applied in this paper. The columns show the method employed for allowing for time-varying betas: The optimal changepoint regression approach; the conditioning variables approach adopted in this paper; a model with the optimal conditioning variables included in the baseline two-factor model, and then the optimal changepoint being estimated; a model with the optimal changepoint included in the baseline two-factor model, and then the optimal conditioning variable being selected; the conditioning variables model estimated using only monthly variables; and a conditioning variables model that allows for time-variation in the intercept as well as the factor loadings. The numbers in each cell represent the proportion of all 9,538 funds for which the bootstrap yields statistically significant results. The test used for the changepoint models is the "avgF" test; and the bootstrap reality check of White (2000) is used for the interaction models. The bottom row of this table reports the proportion of funds for which we would conclude the conditioning variable is significant if we ignored the search process.

	Changepoints	Interactions	Interactions first, add Changepoints	Changepoints first, add Interactions	Interactions, but only monthly	Interactions, allow varying Alpha
Bootstrap	0.309	0.277	0.152	0.301	0.177	0.329
Naive		0.946		0.929	0.935	0.967

Table 7
Comparing Distributions of R-squared and Adjusted R-squared Statistics across Factor Models

This table shows percentile points of the R-squared and Adjusted R-squared distributions across 9,538 funds when applying the different methods to allow for time-varying factor loadings. The columns show the method employed for allowing for time-varying betas: The optimal changepoint regression approach; the conditioning variables (or "interactions") approach adopted in this paper; a model with the optimal interaction terms included in the baseline two-factor model, and then the optimal changepoint being estimated; a model with the optimal changepoint included in the baseline two-factor model, and then the optimal interaction variable being selected; the interaction model estimated using only monthly interaction data; and finally, an interaction based model that allows for time-variation in the intercept as well as the factor loadings. The rows show the statistic being computed; the top panel presents these statistics for R-squared; and the bottom panel presents these statistics for the Adjusted R-squared.

	Constant	Changepoints	Interactions	Interactions first, add Changepoints	Changepoints first, add Interactions	Interactions, but only monthly	Interactions, allow varying Alpha
				R-squared			
10^{th} %	0.082	0.192	0.211	0.268	0.266	0.197	0.247
25^{th} %	0.147	0.272	0.307	0.372	0.363	0.284	0.345
Mean	0.288	0.406	0.454	0.512	0.503	0.424	0.485
Median	0.256	0.388	0.444	0.510	0.499	0.411	0.480
75^{th} %	0.402	0.523	0.594	0.650	0.640	0.552	0.621
90^{th} %	0.544	0.646	0.711	0.755	0.747	0.673	0.731
				Adjusted R-squared			
10^{th} %	0.034	0.098	0.135	0.171	0.158	0.132	0.154
25^{th} %	0.098	0.189	0.230	0.279	0.257	0.221	0.250
Mean	0.247	0.332	0.388	0.430	0.414	0.368	0.402
Median	0.213	0.312	0.371	0.422	0.403	0.349	0.389
75^{th} %	0.365	0.459	0.532	0.574	0.562	0.499	0.542
90^{th} %	0.515	0.598	0.664	0.701	0.690	0.632	0.670

Table 8
Selected Interaction Variables by Strategy

This table shows which interaction variables are most often statistically significant for each of the nine strategies listed in rows. For example, in the Security Selection strategy, 25.328% of funds have statistically significant interaction variables. Of these, 8.934% pick the S&P500 return as the interaction variable, 8.069% pick LIBOR, and 7.637% pick ΔLevel. These three interaction variables are the three most often picked of the entire set of 22 interaction variables, across all individual funds in this strategy.

Strategy	Perc. Sig.	Frequency of Selection					
		1st		2nd		3rd	
Security Selection	25.328	S&P500 Return	8.934	LIBOR	8.069	ΔLevel	7.637
Global Macro	13.021	Default Spread	9.333	Fund Perf (1 M)	9.333	S&P500 Return	6.667
Relative Value	28.205	VIX	14.773	ΔLevel	12.500	Turnover(-1)	6.818
Directional Traders	33.423	LIBOR(-1)	8.434	Mich. Sent.	8.434	Turnover	8.032
Funds of Funds	40.009	ΔLevel	17.550	S&P500 Return	15.430	S&P500 Return(-1)	9.541
Multi-Process	22.989	S&P500 Return	10.556	VIX	9.444	Turnover	8.333
Emerging Markets	20.336	VIX	22.314	ΔLevel	15.703	S&P500 Return	10.744
Fixed Income	24.933	ΔLevel	15.676	VIX	8.649	VIX(-1)	7.568
CTAs and Others	21.343	ΔLevel	10.660	VIX	10.152	LIBOR	9.645