Hedge Fund Predictability Under the Magnifying Glass: Forecasting Individual Fund Returns Using Multiple Predictors*

Doron Avramov†, Laurent Barras‡, and Robert Kosowski§

First version, June 5th 2008;
This version, June 30th 2009

JEL Classification: G11, G23, C12
Keywords: Hedge Fund Performance, Return Predictability, Multiple-Hypothesis Test, False Discovery Rate
PRELIMINARY AND INCOMPLETE

ABSTRACT

This paper develops and applies a framework in which to carefully assess the true forecasting power of economic variables in predictive regressions in a large universe of individual hedge funds. We shed light on the sources and economic interpretation of predictor models that generate superior out-of-sample performance. Using monthly returns for more than 15,000 funds during the period January 1994 through December 2008, we find strong evidence of predictability in the hedge fund industry. We show that the economic value of predictability can be improved by employing a strategy that combines forecasts from several single predictive regressions instead of relying on single or multiple predictive regressions. We investigate the economic and statistical sources of such a *combination strategy*'s superior performance by examining the signal to noise ratio in different components of the predictive regression relationship and by examining the characteristics of funds selected by the strategy. Finally, we use the financial crisis of 2008 as a natural out-of-sample test and show that the combination strategy produces superior risk-adjusted performance during the crisis.

*We thank the seminar participants at Imperial College, HEC-Montreal, McGill University, Tilburg University, University of Rotterdam, and University of Toronto (Rotman) for their comments.
†R.H. Smith School of Business, University of Maryland.
‡Faculty of Management, McGill University
§Imperial College Business School, Imperial College London

I Introduction

This paper develops and applies a framework in which to carefully assess the true forecasting power of economic variables in predictive regressions in a large universe of individual hedge funds. We shed light on the sources and economic interpretation of predictor models that generate superior out-of-sample performance. Using monthly returns for more than 15,000 funds during the period January 1994 through December 2008, we find strong evidence of predictability in the hedge fund industry. We show that the economic value of predictability can be improved by employing a strategy that combines forecasts from several single predictive regressions instead of relying on single or multiple predictive regressions. We investigate the economic and statistical sources of such a *combination strategy*'s superior performance by examining the signal to noise ratio in different components of the predictive regression relationship and by examining the characteristics of funds selected by the strategy. Finally, we use the financial crisis of 2008 as a natural out-of-sample test and show that the combination strategy produces superior risk-adjusted performance during the crisis. We carefully address issues related to potential small sample bias, illiquidity, inference in a large cross-section of funds and show that our results are robust to alternative fund inclusion criteria as well as realistic portfolio rebalancing procedures.

The study of asset return predictability typically consists of assessing the predictive power of various economy-wide variables (e.g., Keim and Stambaugh (1986), Campbell (1987), and Fama and French (1989)) as well as determining whether predictability is consistent with rational asset-pricing by decomposing predictability into its main components, such as time-varying risk premia and factor loadings (Ferson and Harvey (1991, 1999), Kirby (1998), and Avramov (2004)). While these important questions have been raised on several occasions for broad-based stock and bond indices, as well as for mutual funds (Ferson and Schadt (1996)), little is known on hedge fund return predictability. The hedge fund universe is a natural choice to look for predictability due to the quite flexible strategies implemented by hedge fund managers, at least relative to mutual funds and other conservative investment vehicles. Other papers have examined hedge fund index level returns (e.g., Amenc, El Bied, and Martellini (2003), Hamza, Kooli, and Roberge (2006)). Our focus on individual hedge fund returns is motivated by the fact that by simply averaging the slope coefficients across funds, we would lose a lot of information on the predictive ability of each predictor j on the cross-section of funds. While recent papers uncover the benefits from utilizing predictability in the portfolio selection process (e.g. Avramov, Kosowski, Naik, and Teo (2008)), they are not particularly informative regarding the prevalence of predictable hedge funds in the entire population, as well as the importance of different variables in predicting hedge fund returns and alphas (interpreted as managerial skills in market timing and security selection).

This paper proposes an in-depth analysis of the ability of a wide range of predictive variables to forecast returns in a large universe of individual hedge funds. Specifically, for any economic variable that is a potential candidate for forecasting future hedge fund returns, our approach allows to 1) measure the proportions of hedge funds in the population having *truly* predictable returns, 2) determine the components of predictability by estimating the proportions of funds exhibiting *true* alpha predictability.

Measuring such proportions from data seems a priori straightforward. One can simply count the number of funds with sufficiently high (low) estimated regression coefficients, $\widehat{b}$, with respect to any given predictive variable (i.e., funds with significant $\widehat{b}$). Essentially, in implementing such a procedure, we conduct a multiple-hypothesis test, since we simultaneously examine the coefficient of each hedge fund in the population (instead of just one fund). Thus, a simple count of these significant funds is incorrect, as it includes "false discoveries", i.e., funds for which the predictive variable is thought to have some predictive ability, while in reality its true forecasting power is nonexistent (i.e., its true slope coefficient in the predictive regression is zero). One important contribution of our paper is to correctly account for these "false discoveries", leading to a major adjustment from the initial count of significant funds up to 60%.[1]
Moreover, we apply an econometric framework to account for the small sample bias in the fund estimated regression coefficient, $\widehat{b}$ (e.g., Nelson and Kim (1993), Stambaugh (1999)). Small-sample bias is a major concern for hedge funds as their return history is typically short. Indeed, if a large number of fund-estimated coefficients are biased, our assessment of the predictive ability of different predictors can simply be erroneous. To address this issue, we extend the single-asset approach of Amihud and Hurvich (2004; AH hereafter) along two dimensions. First, we consider a large number of assets. Second we formulate an asset pricing specification with time varying parameters, a general version of AH predictive regression. Ultimately we are able to considerably reduce the

[1]Empirically, we find that on average around 20% of the funds have predictable returns, while 80% are unpredictable. Using a large significance level such as 0.4 (so as to detect most predictable funds, the total proportion of "false discoveries" amounts to 32% ($0.8 \cdot 0.4$). Since the total proportion of significant funds equals 52% (32+20), the "false discoveries" represent more than 60% of the significant funds.

bias in both return and alpha predictive regressions. Contrary to the bootstrap, the AH approach is computationally much faster, which is the context of our work is an important advantage due to the large cross-section of funds in our sample (more than 15,000). Using an extensive Monte-Carlo study across a wide range of specifications, we carefully check whether the AH approach is robust to the specific features of individual hedge fund returns (such as departure from normality). We find that the AH approach accurately controls for the small-bias, and exhibit better properties than the bootstrap.

If some economic variables have true predictive ability, an obvious question is whether this information can be utilized by a real-time investor (or a fund-of-fund manager) seeking to improve performance. Indeed, we propose an extensive analysis of the out-of-sample performance of hedge fund conditional strategies. Specifically, for each predictive variable, we form decile portfolios containing the 10% of funds with the highest conditional alpha t -statistics. This predictive signal automatically incorporates the signal of both the unconditional and time-varying alphas in one single measure. In this context, our approach extends previously introduced methodologies applied to asses mutual and hedge fund persistence (e.g., Elton, Gruber, and Blake (1996), Carhart (1997), Kosowski, Naik, and Teo (2007)). In particular, we apply a time-varying, as opposed to a purely static, performance metric.

An essential concern with the performance of a single-predictor conditional strategy is that the investor is subject to specification uncertainty. That is, the investor does not know ex ante which predictor will produce the best ex post performance (e.g., Pesaran and Timmermann (1995)). To address this issue, we also measure the performance of a "combination" strategy which pools the conditioning information across the entire set of predictors, and across individual hedge funds.

Our empirical analysis examines the predictive ability of four economy-wide variables: the default spread, the dividend yield, the VIX range (defined as the one-month high minus low VIX), and the monthly percentage flows to the hedge fund industry. Our universe of funds contains 15,922 funds across ten different investment categories (Convertible Arbitrage, Emerging Markets, Long/Short Equity, Equity Market Neutral, Event Driven, Fixed Income Relative Value, Fund of Funds, Macro, Managed Futures and Multi-Strategy).

Using monthly returns spanning the period January 1994 through December 2008, the strongest evidence of predictability is obtained with the default spread, the VIX, and fund flows. For instance, we find that 22.1 percent of Macro funds and 26.6 percent of Fixed Income Relative Value funds have a truly positive exposure to default spread. This relation is consistent with the strategies followed by these two investment categories, such as fixed-income arbitrage based or FX carry trades (Jylha, Suominen and Lyytinen (2008)). Consistent with Naik, Ramadorai, and Stromquist (2007) who show that past flows negatively affect future performance due to capacity constraints, we find that a substantial proportion of funds (between 11 and 54 percent) are negatively related to lagged flows. Examining alpha predictability using the Fung and Hsieh (2004) seven-factor model, we find that the proportions of funds exhibiting alpha predictability remain nearly unchanged. It implies that the bulk of return predictability is due to time-varying alphas, as opposed to time-varying factor risk-premia.In robustness checks we show that our results are robust to alternative fund inclusion criteria as well as realistic portfolio rebalancing procedures and the use of lower frequency returns.

Measuring the out-of-sample performance of the hedge fund conditional portfolios between January 1997 and December 2008, we find that the "combination" strategy which selects funds based on their conditional alpha t-statistic across all predictors, generates the highest performance, and consistently beats the unconditional strategy across all investment categories. For instance, in the entire population, the annual alpha and Information Ratio differentials are respectively equal to 1.4% (6.8-5.4) and 0.4 (2.5-2.1), and are both significantly different from zero. This is consistent with the previous literature (e.g., Bates and Granger (1969)) showing that combining forecasts help to improve performance. The single-predictor strategies, which only use one single predictor to predict the fund alphas, are generally not able to outperform the unconditional strategy. Empirically, we find that, for most funds, the signal to noise ratio is much higher for the unconditional alpha than for the slope coefficient. This explains why the "combination" strategy selects funds with high unconditional t-statistics (to generate high unconditional alphas), and, then, among these funds, overweights those having a positive slope signal relative to any predictors. For single-predictor strategies, high predictor values increase uncertainty, reduce the fund predictive signals and lead to the selection of funds with lower performance than the unconditional portfolio. Finally, we find that the lowest performance is achieved when using all predictors simultaneously in a multiple predictive regression. One possible reason is that the multiple-predictor estimated alpha is less robust, out-of-sample, than its single-predictor counterpart. Our baseline predictability analysis is carried out for the 1994-2007 period, thus allowing us to use the financial crisis of 2008 as a natural out-of-sample test. We find that the combination strategy generates a higher risk-adjusted performance and Sharpe Ratio in 2008 than the alternative strategies. Further sensitivity tests by investment category show that the combination strategy performs particularly well among the two largest hedge fund categories (Long/Short Equity and Funds of Funds), which goes some way in explaining why the strategy generates superior out-of-sample performance in a sample of all funds.

The paper is structured as follows. In Section II we discuss the methodology. Section III describes the data. Section IV reports our empirical results regarding in-sample predictability and the economic value of incorporating genuine predictability into portfolio formation base on out-of-sample tests. Section V concludes.

II Hedge Fund Predictability

A Predictability in a Multiple Fund Setting

A.1 Return Predictability

To begin, let us consider a cross-section of M individual hedge funds. For each fund i in the population ($i = 1, ..., M$), we use a set of J economic variables, $Z_{j,t}$ ($j = 1, ..., J$), observed at time t to predict its excess return, $r_{i,t+1}$, (over the riskfree rate) between time t and $t+1$:

$$r_{i,t+1} = b_{i,0} + \sum_{j=1}^{J} b_{i,j} \cdot Z_{j,t} + u_{i,t+1}, \tag{1}$$

where $b_{i,0}$ is the intercept and each slope coefficient, $b_{i,j}$, determines the relation between fund i and predictor j–fund i is predictable with respect to $Z_{j,t}$ if $b_{i,j}$ is different from zero. Finally, $u_{i,t+1}$ denotes the fund innovation term.

Since individual funds follow different strategies and trade different assets, the sign and magnitude of the slope coefficient, $b_{i,j}$, is likely to vary across funds. One objective of the paper is to propose a measure of predictability that accounts for this cross-sectional diversity. Specifically, for each predictor j ($j = 1, ..., J$), we decompose the entire fund population into two distinct predictability categories:

•The proportion of unpredictable funds having no relation with predictor j ($b_{i,j} = 0$). We denote this proportion by $\pi_0(j)$.

•The proportion of predictable funds having a non-zero relation with predictor j ($b_{i,j} \lesseqgtr 0$). We denote by $\pi_A^-(j)$ and $\pi_A^+(j)$ the proportion of funds having a negative and a positive relation, respectively.

Of course, we cannot observe the (true) slope coefficient, $b_{i,j}$, and, therefore, we need to infer the proportions of predictable funds, $\pi_A^-(j)$ and $\pi_A^+(j)$, from the data. One obvious procedure is to compute the estimated slope coefficient, $\widehat{b}_{i,j}$, for each fund i, and then consider as predictable the funds in the population with sufficiently low or high $\widehat{b}_{i,j}$ (i.e, funds with significant $\widehat{b}_{i,j}$).

The problem is that, with a limited sample of data, the predictable funds cannot be fully distinguished from the unpredictable ones. To illustrate, Figure 1 shows the hypothetical distribution of the estimated slope coefficient, $\widehat{b}_{i,j}$, of a given fund i across the three possible relation with predictor j (negative, zero, and positive relation). After choosing a significance level, γ^*, we observe whether $\widehat{b}_{i,j}$ lies outside the thresholds implied by γ^* (denoted by $b_{\gamma^*}^-$ and $b_{\gamma^*}^+$), and label fund i "significant" if its $\widehat{b}_{i,j}$ falls into the significance region. As shown by the black and grey areas in Figure 1, a fund with no predictability ($b_{i,j} = 0$) has a positive probability of being a "false discovery", i.e., a fund with a significant estimated slope coefficient, $\widehat{b}_{i,j}$, while its (true) slope coefficient $b_{i,j}$ equals zero. Because we look for predictability across a very large number of funds to look for predictability, this procedure is bound to make some "false discoveries".

Please insert Figure 1 here

Specifically, if we consider the funds with positive $\widehat{b}_{i,j}$, we expect the proportion of significant funds, denoted by $E(S_{\gamma^*}^+(j))$, to be the sum of: 1) the proportion of predictable funds having a positive relation with predictor j, $\pi_A^+(j)$ (that we want to estimate); and 2) a group of "false discoveries", denoted by $E(F_{\gamma^*}^+)$. To measure these false discoveries, we rely on the approach proposed by Barras, Scaillet, and Wermers (2009;BSW hereafter). We know that, at the significance level γ^*, the probability that an unpredictable fund exhibits a positive and significant $\widehat{b}_{i,j}$, equals $\gamma^*/2$ by definition (as shown in Figure 1). Multiplying this probability by the proportion of unpredictable funds in the population, $\pi_0(j)$, we obtain the expected proportion of "false discoveries" with a positive estimated slope coefficient, $\widehat{b}_{i,j}$:

$$E(F_{\gamma^*}^+(j)) = \pi_0(j) \cdot \gamma^*/2. \tag{2}$$

Then, to determine the proportion of predictable funds having a positive relation with predictor j, we simply need to deduce these false discoveries from the significant funds:

$$\pi_A^+(j) = E(S_{\gamma^*}^+(j)) - E(F_{\gamma^*}^+(j)) = E(S_{\gamma^*}^+(j)) - \pi_0(j) \cdot \gamma^*/2. \tag{3}$$

Based on the same procedure, the proportion of predictable funds having a negative relation with predictor j is given by

$$\pi_A^-(j) = E(S_{\gamma^*}^-(j)) - E(F_{\gamma^*}^-(j)) = E(S_{\gamma^*}^-(j)) - \pi_0(j) \cdot \gamma^*/2, \quad (4)$$

where $E(S_{\gamma^*}^-(j))$ denotes the expected proportion of funds with significant and negative $\widehat{b}_{i,j}$, and $E(F_{\gamma^*}^-)$ is the expected proportion of "false discoveries" having a negative $\widehat{b}_{i,j}$.[2]

The procedure to estimating Equations (3) and (4) is straightforward, as it only requires an estimate of the proportion of unpredictable funds in the population, $\widehat{\pi}_0(j)$, as well as the significance level γ^*. Both of them are obtained through simple manipulations of the individual fund p-values associated with the estimated slope coefficient $\widehat{b}_{i,j}$. We provide a brief overview of this estimation procedure in Appendix A, and refer to BSW for further details.

To measure the proportions $\pi_A^-(j)$ and $\pi_A^+(j)$ accurately, we need to set a large significance region (i.e., a high level γ^*), so as to maximize the probability of detecting the truly predictable funds (as shown in Figure 1). But since the proportion of "false discoveries" increases with γ^* (see Equation (2)), it is essential to control for them as they may represent a very important portion of the significant funds. To illustrate, our empirical results (to be presented) reveal that the estimated proportion of unpredictable funds, $\widehat{\pi}_0(j)$, equals 68% on average (across predictors), while $\gamma^* = 0.4$ is a common value. Based on these values, the total proportion of "false discoveries" in the population, $E(F_{\gamma^*}(j)) = E(F_{\gamma^*}^-(j)) + E(F_{\gamma^*}^+(j))$, amounts to 27.2% ($0.68 \cdot 0.4$), and the total proportion of significant funds, $E(S_{\gamma^*}(j)) = E(F_{\gamma^*}(j)) + \pi_A^-(j) + \pi_A^+(j)$, is equal to 59.2% (27.2+(100-68.0)). An estimation of the predictable funds only based on the number of significant funds would be completely misleading, since more than 40% of them (27.2/59.2=46%) are simply false discoveries (i.e., funds that are in reality unpredictable).

A.2 Alpha Predictability

While Equation (1) examines predictability in fund returns, an important issue for investors is to decompose this predictability into its components such as alpha versus risk factor predictability. First, hedge fund managers may have time-varying skills according to the state of the economy (see Christopherson, Ferson, and Glassman (1998), or Avramov and Wermers (2006) for such evidence in the mutual fund industry). Second,

[2] Note that $E(F_{\gamma^*}^-(j)) = E(F_{\gamma^*}^+(j))$ as it should be for a equal-tail two-sided test of predictability: $H_{0,i} : b_{i,j} = 0$ versus $H_{A,i} : b_{i,j} \neq 0$ (see BSW for further discussion).

predictability may be driven by the time-varying premia of the risk factors to which hedge funds are exposed.[3] Using a given asset pricing model (such as the Fung and Hsieh (2004) seven-factor model), we can extend our methodology to disentangle these two sources of predictability by modelling the return of each fund i $(i = 1, ..., M)$ as

$$r_{i,t+1} = \alpha_{i,t} + \beta' F_{t+1}(Z_t) + \epsilon_{t+1} = a_{i,0} + \sum_{j=1}^{J} a_{i,j} \cdot Z_{j,t} + \beta' F_{t+1}(Z_t) + \epsilon_{t+1}. \quad (5)$$

Similar to Shanken (1990) and Avramov (2004), we model the fund i time-varying alpha as a linear function of the predictors, $\alpha_{i,t} = a_{i,0} + \sum_{j=1}^{J} a_{i,j} \cdot Z_{j,t}$, where $a_{i,0}$ is the intercept, and $a_{i,j}$ is the alpha slope coefficient associated with each predictor j $(j = 1, ..., J)$. We denote by $F_{t+1}(Z_t)$ the $K \times 1$ vector of portfolio-based factor excess returns having risk premia expressed as a function of the $J \times 1$ vector of predictors, $Z_t = [Z_{1,t}, ..., Z_{J,t}]'$, by β the $K \times 1$ vector of (time-invariant) fund exposure to the K risk factors, and by ϵ_{t+1} the idiosyncratic fund-specific term.

The procedure to measuring the proportions of funds in the population that exhibit alpha predictability is the same as the one outlined above for return predictability. For a given predictor j, $(j = 1, ..., J)$, we estimate the alpha slope coefficient, $a_{i,j}$, for each fund i in the population $(i = 1, ..., M)$. Then, we count the number of significant funds (i.e., funds with a significant estimated alpha slope coefficient, $\widehat{a}_{i,j}$) and deduce the "false discoveries" (i.e., funds with significant $\widehat{a}_{i,j}$, while their true alphas, $a_{i,j}$, are equal to zero).

B The Economic Value of Predictability

B.1 Forming Predictability-Based Portfolios

If some individual hedge funds exhibit predictability, an important question is to know whether this information can be used in real-time by investors (e.g., institutional investors, fund-of-fund managers) to improve performance. To address this issue, we follow the previous literature on mutual and hedge fund performance by forming decile portfolios (e.g., Elton, Gruber, and Blake (1996), Carhart (1997), Kosowski, Naik, and Teo (2007)). But instead of sorting funds according to a static performance metric (such as the average past return or the estimated alpha), we use the fund time-varying

[3] While there is a large literature on the predictability of broad-based equity and bond factors (e.g., Fama and French (1989), Ilmanen (1995)), as well as size and book-to-market portfolios (e.g., Avramov (2004)) evidence of predictability for the option-based factors considered in hedge fund pricing models (Fung and Hsieh (2001), Agarwal and Naik (2004)) is, to our knowledge, not documented.

expected returns.

At the beginning of a given rebalancing time t, we compute, for each existing fund i ($i = 1, ..., M_t$) its estimated conditional excess mean (over the riskfree rate) for the next period, $\widehat{\mu}_{i,t}$, along with its variance, $\widehat{var}(\widehat{\mu}_{i,t})$. Specifically, if we use a single predictor, say predictor j, to forecast future alphas, we obtain

$$\widehat{\mu}_{i,t} = \widehat{b}_{i,0} + \widehat{b}_{i,j} Z_{j,t}, \quad \widehat{var}(\widehat{\mu}_{i,t}) = X_t' \widehat{V}\left(\widehat{b}_{i,0}, \widehat{b}_{i,j}\right) X_t, \quad (i = 1, ..., M_t), \tag{6}$$

where $\widehat{b}_{i,0}$ and $\widehat{b}_{i,j}$ denote the estimated intercept and slope coefficient, respectively, $X_t = [1, Z_{j,t}]'$, and $\widehat{V}\left(\widehat{b}_{i,0}, \widehat{b}_{i,j}\right)$ is the 2×2 estimated covariance matrix of the regression coefficients (Appendix B.3 explains how to compute $\widehat{V}\left(\widehat{b}_{i,0}, \widehat{b}_{i,j}\right)$). Then, we use the t-statistic of the conditional mean as the fund predictive signal: $\widehat{t}\left(\widehat{\mu}_{i,t}\right) = \widehat{\mu}_{i,t} / \left(\widehat{var}(\widehat{\mu}_{i,t})\right)^{\frac{1}{2}}$. After ranking all funds according to this signal, we form a decile portfolio including the funds with the highest values. This porfolio is held over the next period, after which the selection procedure is repeated (based on the new predictor value at time $t + 1$). The t-statistic can be interpreted as a signal-to-noise ratio which explicitly accounts for the uncertainty surrounding the estimation of the conditional alpha. Such adjustment is crucial, since hedge funds have varying lives and portfolio volatilities depending on their strategy. As a result, the precision of their estimated conditional alphas can differ substantially across funds.[4]

There are two different signals embedded in the fund predictive signal $\widehat{t}\left(\widehat{\mu}_{i,t}\right)$: the unconditional and the slope signals. The unconditional signal measures the fund unconditional performance based on the t-statistic of its unconditional estimated mean, $\widehat{\mu}_i : \widehat{t}(\widehat{\mu}_i) = \widehat{\mu}_i / (\widehat{var}(\widehat{\mu}_i))^{\frac{1}{2}}$. By contrast, the slope signal measures the fund predictable mean component based on the t-statistic of the estimated slope coefficient, $\widehat{b}_{i,j} : \widehat{t}\left(\widehat{b}_{i,j}\right) = \widehat{b}_{i,j} / \left(\widehat{var}(\widehat{b}_{i,j})\right)^{\frac{1}{2}}$. To see this decompositon more clearly, we can use the demeaned predictor value, denoted by $z_{j,t}$, to express the fund predictive signal as

$$\widehat{t}\left(\widehat{\mu}_{i,t}\right) = \frac{\widehat{\mu}_{i,t}}{\left(\widehat{var}(\widehat{\mu}_{i,t})\right)^{\frac{1}{2}}} = \frac{\widehat{\mu}_i + \widehat{b}_{i,j} z_{j,t}}{\left(\widehat{var}(\widehat{\mu}_i) + z_{j,t}^2 \widehat{var}(\widehat{b}_{i,j})\right)^{\frac{1}{2}}}, \tag{7}$$

where we use the fact that $\widehat{\mu}_i$ and $\widehat{b}_{i,j}$ are uncorrelated (see Davidson and MacKinnon (2004), p. 63). When $z_{1,t} = 0$ (the predictor equals its average), the fund predictive

[4] In the empirical results to be presented, we also rank funds according to their time-varying conditional alphas. The procedure is exactly the same as the one outlined in Equation (6), except that the coefficients, $\widehat{b}_{i,0}, \widehat{b}_i$, are replaced with the alpha coefficients shown in Equation (5)

signal only depends on the unconditional signal, i.e., $\widehat{t}\left(\widehat{\mu}_{i,t}\right)=\widehat{t}\left(\widehat{\mu}_i\right)$. On the contrary, as $z_{j,t}$ grows large (and has the same sign as $\widehat{b}_{i,j}$), the predictive signal is mostly driven by the slope signal, as $\widehat{t}\left(\widehat{\mu}_{i,t}\right)$ tends towards $\widehat{t}\left(\widehat{b}_{i,j}\right)$.

Equation (7) reveals that the investor can boost the performance of his portfolio by either selecting funds with high unconditional performance (i.e., high unconditional signals) or by detecting funds which exhibit time-varying conditional mean (i.e., high slope signals). This highlights a crucial point: if we happen to find some predictable funds in the population, this is a necessary, but not sufficient condition to generate a positive economic value. In a multi-fund setting, we have to determine whether a portfolio containing these predictable funds can outperform an unconditional (passive) strategy that selects funds using their unconditional signals only.[5]

B.2 The Combination Strategy

One concern with the single-predictor model shown in Equation (6) is that it is subject to misspecification risk, as the true data generating process is likely to be more complex. Even if this model is correct at a given point in time, its predictive ability may disappear over time due to the investor's learning process or to structural changes in the data (e.g., Timmermann (2007)). When the model is misspecified, the time-varying mean component, $\widehat{b}_{i,j}z_{j,t}$, conveys little information about future performance, and contaminates the fund predictive signal $\widehat{t}\left(\widehat{\mu}_{i,t}\right)$. By using a poor model, the investor tends to exclude funds with high unconditional signals from the portfolio, and replace them with funds whose realized future performance is far from the initial forecast. A second and related concern is that the single-predictor model is subject to specification uncertainty, since there is no theoretical ground to help the investor choose which predictor to use. Therefore, even if a given model performs well out-of-sample, it is not clear whether the investor could have been able to select it in real-time (e.g., Pesaran and Timmermann (1995), Barras (2007)).

An obvious way to address these two issues is to consider a richer predictive model that contain all predictors simultaneously. However, the additional coefficients of this model may not be precisely estimated with the short return history typically available in hedge fund databases. If these estimates are too noisy, they produce low slope signals, and lead again to a poor fund selection.

[5] This contrasts with the single-asset case, where there is a close link between the presence of predictability and its economic value. For instance, Cochrane (1999) shows that the maximum Sharpe ratio, S^*, achieved using a linear predictive model depends on its predictive $R^2: S^*=[(S^2+R^2)/(1-R^2)]^{\frac{1}{2}}$, where S is the Sharpe ratio of the single asset. In a multi-asset setting, such a link may not exist as assets with high predictability may also have low unconditional expected returns.

Alternatively, we implement a "combination" strategy which consists in combining the predictive signals obtained from each individual predictor. Using a simple average, we compute the "combined" predictive signal for each fund i $(i = 1, ..., M)$ as

$$\widehat{t}_{com}\left(\widehat{\mu}_{i,t}\right) = \frac{1}{J}\sum_{j=1}^{J}\widehat{t}_j\left(\widehat{\mu}_{i,t}\right) \quad (8)$$

where $\widehat{t}_j\left(\widehat{\mu}_{i,t}\right)$ is the predictive signal of fund i based on predictor j $(j = 1, ..., J)$.[6] As explained in Clemen (1989) and Timmermann (2006), such forecast combining is an efficient way to robustify the forecast against the misspecification of the individual models. In particular, Hendry and Clements (2002) show evidence that combining provides a good hedge against structural breaks. Finally, the combination strategy is less affected by specification uncertainty, as the investor does not face the difficult task of choosing among the set of J predictors.[7] After ranking all existing funds according to their combined t-statistic, we select the top decile of funds to form the combination strategy.

By reducing specification risk, the combination strategy is more likely to select high unconditional alpha funds having, at the same time, a positive predictable alpha component. To illustrate this point with a simple example, let us consider a given fund i having a very high unconditional signal–we set $\widehat{t}\left(\widehat{\mu}_i\right) = 5.0$, which corresponds in our data to the empirical average of the top decile of funds with the highest unconditional signals. Now what happens if the investor decides to incorporate predictability in his fund selection? Using Equation (7), we plot in Figure 2 the relation between the fund predictive signal, $\widehat{t}_j\left(\widehat{\mu}_{i,t}\right)$, and the predictor value, $z_{j,t}$, used to generate the signal. To ease interpretation, $z_{j,t}$ is expressed in standardized form, such that $z_{j,t} = 1$ indicates that predictor j is one standard deviation higher than its average. Suppose that at time t, the investor observes three different predictors, $z_{1,t}$, $z_{2,t}$, and $z_{3,t}$ (i.e., $J = 3$). The high value taken by predictor 1 ($z_{1,t} = 2$), coupled with its low associated slope signal, $\widehat{t}\left(\widehat{b}_{i,j}\right)$, produces a very low predictive signal, $\widehat{t}_1\left(\widehat{\mu}_{i,t}\right)$, equal to 1.2. Based on this forecast, the investor would certainly not include this fund in this portfolio, although this fund generates a positive unconditional mean almost surely.[8] On the contrary, the forecasts based on predictors 2 and 3 suggest that this fund may provide a positive time-varying mean

[6] While other weighting schemes are possible, the weights have to be estimated from the data. Since the simple average in Equation (8) does not imply any estimation procedure, it often performs better empirically (e.g., Timmermann (2006)).

[7] Forecast combining is also related to Bayesian model averaging, which consists in averaging the model forecast based on a model prior distribution (see Avramov (2002) and Cremers (2002)).

[8] If the fund estimated unconditional mean is and the t-statistic,$\widehat{t}\left(\widehat{\mu}_i\right)$, is equal to 5.0, the probability that the fund has a true mean, μ_i, equal to zero is equal to $2.8e^{-7}$.

component in addition to its unconditional mean. Their slope signals are higher than the one observed for predictor 1, and lead to an increase in the fund predictive signal above the unconditional level ($\widehat{t}_2\left(\widehat{\mu}_{i,t}\right) = 5.4$ and $\widehat{t}_3\left(\widehat{\mu}_{i,t}\right) = 5.1$). By considering many different sources of information, the combination strategy is more robust to the poor predictive signals generated by potentially misspecified models. In our example, the combined predictive signal obtained from Equation (8) is quite high ($\widehat{t}_{com}\left(\widehat{\alpha}_{i,t}\right) = 3.9$), and indicates that this fund is an excellent candidate for fund selection after all.

Please insert Figure 2 here

C Estimation Issues

C.1 Accounting for Small Sample Bias

It is well-known that the estimated slope coefficient, $\widehat{b}_{i,j}$, in Equation (1) is subject to the small-sample bias when its expected value differs from the true value, i.e., $E(\widehat{b}_{i,j}) \neq b_{i,j}$ (Nelson and Kim (1993), Stambaugh (1999)). This bias arises under two frequently met conditions: 1) the $J \times 1$ predictor vector, Z_{t+1}, is persistent, and has an autoregressive structure, such as a VAR(1): $Z_{t+1} = \theta + \Phi Z_t + \upsilon_{t+1}$, where Φ is the $J \times J$ companion matrix, and υ_{t+1} is the $J \times 1$ predictor innovation vector; 2) the hedge fund i innovation, $u_{i,t+1}$, is contemporaneously correlated with υ_{t+1}: $E\left(u_{i,t+1}\left|\upsilon_{t+1}\right.\right) = \phi_i' \upsilon_{t+1}$, where ϕ_i denotes the $J \times 1$ innovation coefficient vector.[9] In this case, the $J \times J$ estimated companion matrix, $\widehat{\Phi}$, is biased in small samples (because $E\left(\upsilon_{t+1}\left|Z_0, ..., Z_T\right.\right) \neq 0$), and $\widehat{b}_{i,j}$ inherits some of the bias in $\widehat{\Phi}$.

While this bias disappears in large samples, it is an important concern for hedge funds because their return history is typically short (72 months on average in our sample). Since the estimated slope coefficients may differ radically from their true values, distinguishing between predictable and unpredictable funds from the data can be very difficult.

When multiple predictors are used as in Equation (1), Amihud and Hurvich (2004;AH hereafter) show that the bias in the estimated slope coefficient associated with predictor j ($j = 1, ..., J$), can be written as

$$bias(\widehat{b}_{i,j}) = E(\widehat{b}_{i,j} - b_{i,j}) = \sum_{k=1}^{J} E\left(\widehat{\rho}_{k,j} - \rho_{k,j}\right) \phi_{i,k}, \tag{9}$$

[9] If Z_t truly predict future returns, we expect to see a contemporaneous correlation between υ_{t+1} and $u_{i,t+1}$. The predictor innovation, υ_{t+1}, captures changes in expected returns, which in turn induces a shock to the contemporaneous hedge fund return.

where $\widehat{\rho}_{k,j}$ and $\rho_{k,j}$ denotes the k^{th} row, j^{th} column element of the matrices $\widehat{\Phi}$ and Φ, respectively, and $\phi_{i,k}$ is the k^{th} element of the innovation vector ϕ_i. Equation (9) can be interpreted as an omitted variable bias, since $\widehat{b}_{i,j}$ captures the influence of the omitted innovation vector, $\upsilon_{t+1,}$ on $r_{i,t+1}$ (represented by the vector ϕ_i). The bias in $\widehat{b}_{i,j}$ depends on each bias term, $E\left(\widehat{\rho}_{k,j} - \rho_{k,j}\right)$, which in turn is a complex function of Φ and the covariance matrix of υ_{t+1} (Nicholls and Pope (1988)). Therefore, it is generally difficult to understand the drivers of this bias, and to predict its sign (Ang and Bekaert (2007)). However, many papers find that Φ is nearly diagonal as most predictors exhibit high level of persistence (e.g., Campbell (1991) or AH). In this case, the analytical bias formula proposed by Stambaugh (1999) in the single-predictor case, $-\frac{(1+3\rho_j)}{T_i}\phi_{i,j}$, can be used to approximate Equation and reveals that the bias in $\widehat{b}_{i,j}$ is high (in absolute value) when 1) the (true) persistence coefficient, ρ_j, is high; 2) the (true) innovation coefficient, ϕ_j, is high (in absolute value); and 3) the number of fund i return observations, T_i, is low.

To correct for small-sample bias in the data, we use the simple approach proposed by AH. The intuition behind this approach is to find a proxy, denoted by υ^c_{t+1}, for the unobservable innovation vector υ_{t+1} that causes the bias. This approach consists in three steps. First, we estimate the parameters of the VAR(1), and apply an analytical bias correction to obtain the bias-corrected estimates, $\widehat{\theta}^c$ and $\widehat{\Phi}^c$ (the details are shown in Appendix B.1). Second, we compute the proxy as $\upsilon^c_{t+1} = Z_{t+1} - \widehat{\theta}^c - \widehat{\Phi}^c Z_t$. Finally, we insert the $J \times 1$ vector υ^c_{t+1} into Equation (1) as an additional explanatory vector:

$$r_{i,t+1} = b^c_{i,0} + \sum_{j=1}^{J} b^c_{i,j} Z_{j,t} \; + \phi_i^{'} \upsilon^c_{t+1} + e_{i,t+1}, \tag{10}$$

where $b^c_{i,0}$ is the intercept, $b^c_{i,j}$ the bias-corrected slope coefficient associated with predictor j ($j = 1, ..., J$), and $e_{i,t+1}$ is the innovation term. Since we use a proxy for υ_{t+1} (instead of its true value), the bias-corrected estimated estimated coefficient, $\widehat{b}^c_{i,j}$ is not bias-free. However, the remaining bias, given by $E(\widehat{b}^c_{i,j} - b_{i,j}) = \sum_{k=1}^{J} E\left(\widehat{\rho}^c_{k,j} - \rho_{k,j}\right)\phi_{i,k}$, is driven to zero as the bias-corrected values, $\widehat{\rho}^c_{k,j}$, get closer to the true values, $\rho_{k,j}$. In Appendix B, we show how to apply the same procedure for the alpha predictive regression in Equation (5), and how to compute the slope coefficient t-statistics and p-values used to measure the proportions of predictable funds and to form the hedge fund portfolios.

While an alternative bootstrap approach would be possible, the AH approach is computationally much faster. This computational efficiency has strong appeal because of the great number of funds that we examine in the paper (more than 15,000). To determine wether the AH approach is robust to the specific distributional features of hedge funds, such as non-normality (e.g., Kosowski, Naik, and Teo (2007)), we run a extensive Monte-Carlo analysis calibrated on hedge fund data. The results described in Appendix C show that accounting for the small sample bias is important, especially for highly persistent predictors, and that the AH approach compares favorably with the bootstrap.

C.2 Accounting for Illiquidity

While many hedge funds invest in traditional asset classes, some of them also trade more specific assets, such as emerging market debt, asset-backed securities, or over-the-counter derivatives. While these illiquid assets are affected by non-synchronous trading and stale prices, they also facilitates return misreporting documented by Bollen and Pool (2009). For these reasons, illiquidity tends to smooth returns over time, and induce serial correlation (Getmansky, Lo, and Makarov (2004)).[10] While the presence of serial correlation in the residuals, $e_{i,t+1}$, in Equation (10) does not change the value of estimated slope coefficient, $\widehat{b}^{c}_{i,j}$, it affects its associated t-statistic and p-value.

To explicitly account for this potential correlation, we use an AR specification. Specifically, for each fund i in the population ($i = 1, ..., M$), we first compute the residual from Equation (10), and regress it on its own lagged values to obtain consistent estimators of AR coefficients. Our analysis detailed in Appendix B shows that 26.2% and 37.0% of the funds have a non-zero first and second lag coefficients, respectively. Consistent with Getmansky, Lo, and Makarov (2004), we find that investment categories such as Convertible Arbitrage, Emerging Markets, and Fixed Income Arbitrage have the highest proportion of funds with non-zero first lag coefficient (65.5%, 35.7%, and 35.5%, respectively). However, we find little evidence of third lag correlation–only 2.1% of the funds in the population have a third-lag coefficient different from zero (this finding is confirmed across the different investment categories). Based on these results, we model the dependence structure with an AR(2) specification: $e_{i,t+1} = \rho_{i,1}e_{i,t} + \rho_{i,2}e_{i,t-1} + \xi_{i,t+1}$.

III Description of the Data

We evaluate the performance of hedge funds using monthly net-of-fee returns of live and dead hedge funds reported in the BarclayHedge, TASS, HFR, CISDM and MSCI and

[10] Another reason for the presence of serial correlation is spurious regression (Ferson, Sarkissian, and Simin (2003)). If the predictive model in Equation (1) is misspecified and the true (unobservable) expected return is persistent over time, the fund residual inherits this persistence, and is serially correlated.

BarclayHedge datasets over January 1990 to December 2008 - a time period that covers both market upturns and downturns, as well as relatively calm and turbulent periods. The union of the TASS, HFR, CISDM, MSCI databases represents the largest known dataset of the hedge funds to date. Our initial fund universe contains more than 15,000 live and dead hedge funds. While there are overlaps among the hedge fund databases, there are many funds that belong to only one database. This highlights the advantage of obtaining our funds from a variety of data vendors.

To allow a detailed interpretation of predictability results by strategy we choose to group funds into finer categories than many previous studies. We group funds into 10 categories: Convertible Arbitrage, Emerging Markets, Long/Short Equity, Equity Market Neutral, Event Driven, Fixed Income Relative Value, Fund of Funds, Macro, Managed Futures and Multi-Strategy.

Convertible Arbitrage funds exploit mispricing in the convertible bond market such as underpriced implied volatility, for example. Emerging Markets funds pursue a range of (historically mostly long-only) strategies in emerging markets. Long-Short Equity funds take long and short positions in undervalued and overvalued stocks, respectively, and reduce systematic risks in the process. Equity Market Neutral funds are similar to Long/Short Equity funds in that they take long and short positions but differ in that they typically follow more high frequency signals and systematic trading strategies. Event Driven funds which include Merger Arbitrage funds monitor corporate events and restructurings and employ multiple strategies usually involving investments in opportunities created by significant transactional events, such as spin-offs, mergers and acquisitions, bankruptcy reorganizations, recapitalizations, and share buybacks.

Fixed Income Relative Value funds follow a range of spread strategies in different parts of the fixed income market to benefit from relative mispricing related to credit risk or the shape of the yield curve. Macro funds differ from Fixed-Income Relative Value funds in that they often take directional positions in fixed income markets that depend on global macroeconomic variables and often reflect a medium to long-term outlook. Managed Futures Funds share some similarities with macro funds in that they use relatively liquid instruments such as futures and often pursue directional strategies, but they differ in the type of signals used which tend to be more high frequency and quantitative in nature. Multi-strategy funds are similar to funds of funds in that they attempt to achieve diversification across strategies, but unlike the latter they often follow more specialized strategies that - given fewer constraints on redemptions and inflows than fund of funds - can respond quickly to tactical signals.

The total population amounts to 15,922 funds. The majority of them belong to the Funds of Funds (3611 funds) and Long/Short Equity categories (3,007), followed by Multi-Strategy (1883), Managed Futures (1174), Fixed Income Relative Value (673), Event Driven (608), Emerging Markets (600), Macro (599), Equity Market Neutral (463), and Convertible Arbitrage (279). Other categories account for the remaining 3025 of the 15,922 funds. For rest of the paper, we focus on the funds in one of the 10 major categories above.

The finer classification of hedge fund categories is important for a detailed economic interpretation of any predictive relationships that we uncover. It is also useful for diagnostic tests such as serial correlation that may be related to the holding of illiquid securities. The category Event Driven, for example, may be expected to a priori exhibit stronger return serial correlation due to relatively illiquid securities. The opposite can be expected from the category Managed Futures.

It is well known that hedge fund data are associated with many biases (Fung and Hsieh (2000)). These biases are driven by the fact that due to lack of regulation, hedge fund data are self-reported, and hence subject to self-selection bias. To ensure that our findings are robust to incubation and backfill biases, we repeat our analysis by excluding the first 12 months of data. These adjustments do not change our conclusions quantitatively and are available from the authors upon request.

In addition, since most database vendors started distributing their data in 1994, the datasets do not contain information on funds that died before December 1993. This gives rise to survivorship bias. We mitigate this bias by examining the period from January 1994 onwards in our baseline results. We require each fund to have at least 36 monthly return observations in order to estimate the coefficients of the (return and alpha) predictive regressions in Equation (1) and (5).

We use four instruments to predict future hedge fund returns: default spread, dividend yield, VIX and flows. Default spread is the yield differential between Moodys BAA-rated and AAA-rated bonds. It captures conditions in fixed income markets and is closely correlated with the term spread. The dividend yield is the total cash dividends on the value-weighted CRSP index over the previous 12 months divided by the current level of the index. The dividend yield and the default spread are included since they are closely related to the business cycle. The dividend yield tends to peak in recessions. The VIX is defined as the one-month lagged VIX from the CBOE[11]. We include the VIX since volatility helps to capture some of the non-linear in hedge fund returns such as that observed in trend-following funds. Flows are the monthly capital flows into hedge funds, calculated as the value-weighted percentage in- and outflows into the hedge funds

[11] See http://www.cboe.com/micro/vix/historical.aspx.

in our database. The inclusion of capital flows is economically motivated by the potential existence of capacity constraints in the hedge fund industry (Naik, Ramadorai, and Stromqvist (2007)).

Figure 3 shows that during the financial crisis of 2008 the predictor variables such as dividend yield, default spread and VIX exhibited extreme deviations from the long-term historical average. When including 2008 we reject the hypothesis that all predictor variables are stationary during the sample. For these reasons we choose our baseline period as 1994-2007 and carry out a detailed robustness test with respect to the inclusion of 2008. This allows us to use 2008 as an additional out-of-sample test of the predictive relationships that we identify. Another reason for excluding 2008 is that the long-term relationship between hedge fund returns and predictor variables may be better captured by excluding the year 2008 which is an important but rare event.

Panel A of Table I reports descriptive statistics for the hedge funds included in our sample between January 1994 and December 2007. For each hedge fund category, we report the cross-sectional median of the annualized fund mean excess return (over the riskless rate), the standard deviation of the fund excess return, as well as skewness and kurtosis. Long/Short Equity and Emerging Markets funds exhibit the highest median return while Emerging Markets and Managed Futures exhibit the highest volatility over the period. Consistent with the previous literature, the average FH alpha is positive across all investment categories. Its highest level is observed for Multi-process funds ($\alpha = 7.2$ percent per year), and Long/Short Equity funds ($\alpha = 6.7$ percent).

Please insert Table I here

In Panel B, we show descriptive statistics for the predictor variables.

The degree of predictor persistence has an important impact on the small-sample properties of the estimated slope coefficient (Section II.B). Consistent with previous studies, we find that the default spread, dividend yield and VIX[12] exhibit high positive autocorrelation ($\rho = 0.96$, 0.97 and 0.84) while fund flows exhibit low autocorrelation ($\rho = 0.26$).

Finally, Panel C contains summary statistics for the risk factors included in the Fung and Hsieh (2004; abbreviated as FH) seven factor model. SNPMRF is the S&P 500 return minus risk free rate, SCMLC is the Wilshire small cap minus large cap return, BD10RET is the change in the constant maturity yield of the 10–year Treasury appropriately adjusted for duration, BAAMTSY is the change in the spread of

[12] See Drechsler and Yaron (2008) for VIX.

Moody's Baa minus the 10–year Treasury also adjusted for duration, PTFSBD is the bond PTFS, PTFSFX currency PTFS, PTFSCOM is the commodities PTFS, where PTFS is primitive trend following strategy (see FH). While the equity market and bond factors generate positive risk premia, the average excess returns of the size factor as well as the trend following strategies are strongly negative over our sample period.

IV Empirical Results

A Measuring Hedge Fund Predictability

A.1 Individual Fund-Level Predictability

We start our empirical analysis by examining individual fund-level excess return predictability (Equation (1)) over the entire period January 1994-December 2007. Other papers have examined index level returns. However, by simply averaging the slope coefficients across funds, we would lose a lot of information on the predictive ability of each predictor j on the cross-section of funds.

In Panel A of Table II we report the proportions of funds in different hedge fund categories that exhibit genuine predictability after accounting for "false discoveries" in the predictive relationships. These estimated proportions, $\widehat{\pi}_A^-(b_j)$ and $\widehat{\pi}_A^+(b_j)$, are calculated using Equations (4) and (3), where the fund estimated slope coefficients are computed using the bias-corrected approach explained in the appendix.

Please insert Table II here

First, we find strong evidence of positive return predictability when using the default spread as a variable in the multiple predictive regression. All but one category show a high proportion of funds with positive return predictability with respect to the default spread as captured by $\widehat{\pi}_A^+(b_j)$. For instance, we find that 51.11 percent and 22.09 percent of the Emerging Markets and Macro funds genuinely exhibit positive predictable returns. This exposure is likely to be driven by the strategies followed by these funds. The Macro category includes global macro funds that, among other strategies, follow carry trade strategies in FX markets. A widening of credit spreads is likely to coincide with an increase in risk aversion and unwinding of carry trades, which increases the future expected returns on carry traders (Jylha, Suominen, and Lyytinen (2008), Brunnermeier, Nagel and Pedersen (2008)). Similarly, Emerging Markets funds are affected by flights to quality that lead to outflows from emerging debt and equity markets. Predictability in emerging sovereign debt markets based on the default spread has recently been documented by Jostova (2006).[13] Convertible bond funds returns are also strongly predicted by the credit spread. Since a long position in a convertible bond is exposed to credit risk, a widening of credit spreads may be consistent with higher expected returns on corporate bonds. Some standard fixed income fund strategies consist of leveraged spread trades that exploit mispricing between low grade and high grade bonds, bonds of different maturity or different parts of the fixed income market. As we would expect, 22.57% of Fixed Income Relative Value funds exhibit strong return predictability with respect to the default spread.

To get a sense of the magnitude of the funds' exposure to the different predictors, we also report, in columns adjacent to the proportion of negative and positive funds, the cross-sectional average as well as 25th and 75th percentile (in parentheses) of the fund bias-corrected estimated slope coefficients, $\widehat{b}^c$. The estimated coefficients are standardized (by multiplying the original estimate by the predictor standard deviation), so that they correspond to the change in fund monthly excess returns for a one standard deviation increase in the predictor value. Except in the few cases (such as the 35 basis point average exposure of Long/Short Equity funds to fund flows and the 60 basis point exposure of Emerging Markets funds to the default spread), we find that the average slope coefficients are of economically small magnitude. However, the cross-sectional standard deviation is generally large, and implies that individual funds can be strongly impacted by changes in the predictor values. Specifically, for some Emerging Markets funds, a one standard deviation change in the credit spread changes their future expected excess returns by approximately 1%.

Second, we find that increases in the VIX decrease the excess returns for a large proportion of funds during next period. For instance, 40.50 percent of Emerging Markets funds and 41.08 percent of Event Driven funds exhibit negative predictability with respect to the VIX. The Convertible Arbitrage and Fixed Income category (which contains capital structure arbitrage funds) also exhibits predictability with respect to the VIX. This is consistent with some of the non-linear return patterns documented for these funds (Lhabitant (2006)). Convertible bond funds often exploit mispriced volatility in convertible bonds and can therefore be expected to be sensitive to changes in the VIX (Agarwal, Fung, Loon and Naik, 2009). Increases in the VIX may indeed reduce

[13] Emerging market equity returns have higher serial correlation than developed market returns. Serial correlation emerging markets equity returns has been attributed to infrequent trading and slow adjustment to current information (Harvey, 1995; Kawakatsu and Morey, 1999). The literature on stock selection in emerging markets suggests that relatively simple combinations of fundamental characteristics can be used to develop portfolios that exhibit considerable excess returns to the benchmark (Achour et al., 1999; Fama and French, 1998; Rouwenhorst, 1999).

opportunities of *cheap* volatility and therefore explain the 28.6 percent of convertible bond fund that are negatively predicted by the VIX.

Third, the lagged aggregate flows to the hedge fund industry has a negative impact on future returns. This result is consistent with Naik, Ramadorai, and Stromquist (2007), who find that capacity constraints caused by excessive inflows lead to a decrease in future performance. 53.08% and 41.87% of Emerging Markets and Long Short Equity funds are negatively predicted by high fund flows, as is the case for all fund categories.

In order to measure alpha predictability, we add the FH risk factors to the predictive regression (Equation (5)). For each category, Panel B of Table V shows the estimated proportions of funds having alphas negatively and positively related to the different predictors, $\widehat{\pi}_A^-(a_j)$ and $\widehat{\pi}_A^+(a_j)$. For Long/Short Equity funds for example, a large proportion of funds exhibit statistically significant negative alpha predictability with respect to fund flows (29.13 percent) and the VIX (26.68 percent) and positive alpha predictability with respect to the default spread (24.26 percent). The coefficient estimates show that a one standard deviation increase in fund flows and volatility leads to a 21 and 18 basis point decrease in Long/Short Equity fund returns respectively. Similarly, a one standard deviation increase in the default spread increases fund returns by 13 percent.

Comparing these results with those shown in Panel A, we find that the estimated proportions remain relatively unchanged. This result implies that the bulk of return predictability is due to time-varying alphas. This interpretation would be strengthened if we found that hedge fund benchmark factors are nearly unpredictable and funds' betas with respect to the benchmark factors were low. Indeed, this is what find in the following Table III.

Table III shows the results of regressing each of the 7 FH benchmark factors on four predictor variables. An examination of the resulting regressions is that there is little evidence of factor predictability. In Panel A only three of the 28 slope coefficient p-values indicate statistically significant predictability at the ten percent significance level. To assess how important predictability captured by the predictors is relative to the unconditional alpha, we report the ratio of the two in Panel B of Table **??** (Columns 8 to 11). For each fund, we divide the absolute value of the slope coefficient by the absolute value of the alpha coefficient. There are 10 individual categories and 4 predictors. For 31 of the 40 different combinations we find that ratio is less than 50 percent which indicates that the alpha coefficient is economically more important the the slope coefficient. The finding that most of the return predictability in hedge fund returns is due to alpha predictability is consistent with results reported by Avramov, Kosowski, Naik and Teo (2008) who find that the portfolio of a Bayesian investor that allows for alpha predictability outperforms that of an investor that does not allow for alpha predictability.

Please insert Table III here

When examining return predictability there are two reasons for examining predictability at different return frequencies. First, since the realistic portfolio rebalancing frequency is annual, there are limits to exploiting the full predictability present at monthly frequency. Second, the data generating process may differ depending on the frequency. Hedge fund investors are likely to also take into account longer term returns, since monthly returns may be affected by temporary return fluctuations. Therefore, in Table IV we compare return predictability at the quarterly frequency to our baseline results that use monthly returns. We find that the conclusions based on quarterly returns are qualitatively similar to our baseline results. The predictability coefficient at both frequencies have usually the same sign and evidence of predictability at the monthly level is generally stronger than at the quarterly level. 35 of the 40 regressions have higher median coefficients at the monthly than the quarterly level. A one standard deviation increase in flows leads to a 35 (22) basis point increase in fund returns at the monthly (quarterly) level. A one standard deviation increase in the default spread increases the return of macro funds next period by 13 (14) basis points using monthly (quarterly) returns.

Please insert Table IV here

A.2 Price Impact of Unexpected Changes in Predictor Values

In Progress

Please insert Table V here

B Measuring the Economic Value of Predictability

B.1 Out-of-Sample Performance Analysis

In Section II.B, we discuss different conditional strategies that all consist of selecting the top decile of funds with the highest conditional mean predictive signal defined as $\widehat{t}\left(\widehat{\mu}_{i,t}\right) = \widehat{\mu}_{i,t} / \left(\widehat{var}(\widehat{\mu}_{i,t})\right)^{\frac{1}{2}}$, where $\widehat{\mu}_{i,t}$ denotes fund i conditional excess mean (over the riskfree rate), and $\widehat{var}(\widehat{\mu}_{i,t})$ its estimated variance (see Equation (6)). The first set of conditional strategies are single-predictor strategies in which the predictive signal is computed using one of the four possible predictors (Dividend yield, Default spread, Volatility, Aggregate flow). The second set of strategies are based on multiple predictors. While the "All predictor" strategy estimates the predictive signal using all predictors simultaneously in a multiple regression, the combination strategy computes the fund predictive signal by averaging across the four single-predictor signals (see Equation (8)). Each of these conditional strategies is compared to the unconditional strategy, which simply ranks funds based on their unconditional mean predictive signal, $\widehat{t}\,(\widehat{\mu}_i) = \widehat{\mu}_i / \left(\widehat{var}(\widehat{\mu}_i)\right)^{\frac{1}{2}}$, where $\widehat{\mu}_i$ denotes fund i unconditional excess mean, and $\widehat{var}(\widehat{\mu}_{i,t})$ its estimated variance.

The construction of the different portfolios proceeds as follows. At the end of each year, we estimate the predictive and unconditional signals of each existing fund using the past three-year returns. The first portfolio formation date is December 31, 1996, while the final formation date is December 31, 2007 (the first 3 years of our sample between January 1994 and December 1996 are used to obtain the initial estimations). If a selected fund does not survive during the holding period, its weight is reallocated to the remaining funds to mitigate survival bias. In the out-of-sample analysis we pay particular attention to practical constraints that an investor may face if she implemented the strategy. Institutional investors and Funds of Funds cannot invest in closed funds and typically do not invest in small funds. Therefore we exclude closed funds and the smallest third of funds as described in Section II. Funds are ranked each year by Assets under Management (AuM) and the bottom third of fund is excluded. Some previous studies excluded funds with less than \$20 million AuM. The advantage of our dynamic filter is that it implicitly takes into account inflation and the growth in average AuMs. Moreover, in 2002 our dynamic requirement leads to the exclusion of the same number of funds as the static \$20 million AuM filter used in previous studies. Since the out-of-sample tests simulate a funds of funds approach we also excluded funds of funds and focus on hedge funds. To make sure that the constructed portfolios would be feasible in practice we also impose a constraint of 20 and 100 funds on the minimum and maximum number of funds included in the portfolio.[14] In sensitivity tests shown below, we find that specification changes to this baseline case do not change our results qualitatively.

In Panel A of Table VI, we compare the out-of-sample performance of the unconditional and conditional portfolios for all funds in the population. We report the annualized excess return, $\widehat{\mu}$ (minus the riskfree rate), total standard deviation, $\widehat{\sigma}_{tot}$, and Sharpe ratio, SR= $\widehat{\mu}/\widehat{\sigma}_{tot}$, the estimated annualized Fung and Hsieh (FH) alpha, $\widehat{\alpha}$, residual standard deviation, $\widehat{\sigma}_{res}$, and information ratio, IR= $\widehat{\alpha}/\widehat{\sigma}_{res}$. For each of these performance metrics, we report in parentheses the one-sided p-values indicating whether

[14] These are conservative diversification bounds, as the typical number of funds included in funds of funds is around 40 funds (Lhabitant (2007)).

the conditional strategy outperforms the unconditional strategy. We also compute the 5 and 95 percent quantiles of the monthly portfolio returns. While the Sharpe ratio indicates the risk-return profile of the strategy, the Information ratio determines how the Sharpe ratio of an uninformed strategy formed with the basis assets (i.e., the FH risk factors) increases after optimally combining it to the conditional portfolio (Treynor and Black (1973)).

Table VI shows that the unconditional portfolio's out-of-sample annualized alpha and IR are 5.4% and 2.1, respectively. This is much higher than the performance of the value-weighted and equal-weighted hedge fund indices. Are the conditional strategies able to provide any additional performance? Examining the single-predictor portfolios, we find that, while some of them (such as Default or Flows) generate significantly higher alphas than the unconditional strategy, they do not outperform the unconditional strategy in terms of risk-return tradeoff or Information ratio. Even worse, using all predictors simultaneously to predict fund alphas (the "All predictors" strategy) leads to the worst performance ($IR = 1.4$). One possible interpretation is that since the hedge fund return history is generally low, conditional means using multiple regression may be poorly estimated, leading to noisy predictive signals.

There is one conditional strategy–the combination strategy–which dominates the unconditional portfolio and all the other single and multiple predictor strategies in terms of Information ratio and Sharpe ratio (SR=1.8, IR=2.5). The combination strategy's estimated annual alpha is almost 6.8% and is thus the second highest (after Volatility).

Please insert Table VI here

This superior performance comes with several other advantages from the investor perspective. First, as explained in Section II.B, this strategy is immune to specification uncertainty, since the investor does not have to choose among predictive variables. It is important to note that we would not expect the combination strategy to outperform every year since in certain years one predictor may play a more important role than other predictors. However, if model uncertainty plays an important role on average - as many studies document (see Avramov (2002), for example) - then we would expect combination strategy to generate superior performance. Second, this conditional strategy does not involve extensive (and possibly unrealistic) portfolio turnover as Panel B shows. The combination strategy has the second lowest (58.7%) turnover of constituent funds among the seven strategies considered while the "all predictors" strategy generates the highest and therefore potentially most costly turnover (of 89.6%). An examination of the risk exposures in Panel B shows that the combination strategy portfolio has the lowest exposure to the size factor (β_{size} =0.07), the term spread factor (β_{term} =0.03) and the second lowest exposure to the market factor (β_{market} =0.11).

B.2 Sources of the Superior Performance of the Combination Strategy

Unconditional versus Slope Signals

To shed further light on the relative performance of the different strategies we analyze the importance of the slope coefficient in the predictive regression relative to the unconditional mean. As an alternative to our conditional strategies based on the conditional mean predictive signal, we therefore rank funds according to their slope signals. The results shown in Table VII reveal that only using the slope signal generates lower alphas and information ratios than the baseline strategies. In addition, the combination strategy generates an Information ratio of 0.9 (compared with a value of 2.5 in the baseline case in Panel A). Hence, in order to generate positive performance, the conditional strategy must use the information signals contained in both the unconditional mean, as well as its time-varying components.

Why do the slope signal strategies perform so poorly? One way to answer this question is to compare the characteristics of the funds included these portfolios. Specifically, for each month t, we measure the fund average unconditional mean for each portfolio: $\widehat{\mu}_{p,t} = (1/N_t)\sum_{i=1}^{N_t}\widehat{\mu}_i$, where N_t is the number of funds included in the portfolio, and $\widehat{\mu}_i$ its estimated unconditional mean (over the previous three-year period). By averaging $\widehat{\mu}_{p,t}$ over time, we obtain a measure $\widehat{\mu}_p$ of the unconditional mean for the "average fund" included in the portfolio. Proceeding along the same line, we can examine the exposure to each predictor. For each month t, we measure the fund average slope coefficient for each portfolio: $\widehat{b}_{p,t} = \left((1/N_t)\sum_{i=1}^{N_t}\widehat{b}_{i,j}\right) I_{Z_{j,t}-\overline{Z}}$, where N_t is the number of funds included in the portfolio, $\widehat{b}_{i,j}$ is the fund estimated slope coefficient (over the previous three-year period), $I_{Z_{j,t}-\overline{Z}}$ is a function that take the value 1 if the predictor is above average and -1 otherwise. $\widehat{b}_{p,t}$ is positive only if the portfolio has the right exposure to the predictor j : to benefit from potential predictability, the portfolio must select funds with positive $\widehat{b}_{i,j}$ when the predictor is above average (and vice-versa). By averaging $\widehat{b}_{p,t}$ over time, we obtain a measure $\widehat{b}_p$ of the slope coefficient for the "average fund" included in the portfolio (i.e., a measure of exposure to the predictor).

The main reason for the poor performance of the "slope signal" portfolios is that they tend to select funds with much lower unconditional mean than those in the "predictive signal" portfolios. By trying to bet more aggressively on potential predictability, these strategies lose between 0.28% and 0.48% per month compared to the "predictive signal" strategies. In addition, they fail to generate a much stronger exposure to the predictor, as $\widehat{b}_p$ is even higher for the "predictive signal" strategies in two cases (Dividend yield and Aggregate flow). One possible explanation is the annual rebalancing. Over one year, the predictor might change substantially, implying that the funds selected initially might not have the correct exposure anymore (this is especially true for Aggregate flow, which is the least persistent variable)

Please insert Table VII here

Single-Predictor versus Combination Strategy

Our previous results reveal that few single-predictor strategies are able to significantly outperform the unconditional strategy. One possible reason is that the predictive signal of these strategies is too low to generate consistent performance over time. To address this issue, we examine the relation between the portfolio predictive signal and performance.

During each month from January 1997 to December 2008, we compute the portfolio predictive signal, $\widehat{t}_{p,t}$, as the average signal of the funds it includes: $\widehat{t}_{p,t} = \sum_{i=1}^{N_t} \widehat{t}\left(\widehat{\mu}_{i,t}\right)$, where N_t is the number of funds included in the portfolio at time t. We use the label *signal* in this context since each strategy uses $\widehat{t^j}$ to select funds into portfolios. After calculating the signal of the unconditional portfolio, $\widehat{t}_{u,t} = \sum_{i=1}^{N_t} \widehat{t}\left(\widehat{\mu}_i\right)$, we measure the monthly Predictive Signal Differential (PSD) as $\widehat{t}_{p,t} - \widehat{t}_{u,t}$. Then, we rank these signal differences in increasing order, and form two groups of equal length. The months corresponding to the lowest values are included in the low signal state (L), while those with the highest values belong to the high signal state (H). In row 1 of Table VIII, we report the average value of PSD in the low and high states across predictors and investment categories. In the two states (low and high), we find that the PSD is most of time negative, indicating that the funds slope signals, $\widehat{t}_j\left(\widehat{b}_{i,j}\right)$, are generally lower than their unconditional signals, $\widehat{t}\left(\alpha_i\right)$. While PSD is mostly negative, we still observe a huge increase as we move from the low to high state–while most values range between -1.6 and -2.6 in the low state, they get closer to zero in the high state (generally between -0.2 and 0.2).

In Row 2 of Table VIII, we analyze the absolute value of each predictor, $|z_{j,t}|$, in the low and high state. The predictor is standardized, so that a value $|z_{j,t}| = 1$ indicates that the predictor value, $Z_{j,t}$, is one standard deviation above or below its average. Our main finding is that the predictor always takes more extreme values during the low state. Intuitively, one might expect that a higher $|z_{j,t}|$ has a positive impact on performance, as the time-varying component in alphas gets larger. However, in a world where the unconditional signal is more precise than the slope signal, high values for $|z_{j,t}|$ are associated with increased uncertainty, reduce the fund predictive signals (see Figure 2), and ultimately lead to the selection of funds with lower performance than the unconditional portfolio.

Row 3 reports, in each state, the change in weights between the conditional and unconditional portfolios, measured for each month as $|w_{c,t} - w_{u,t}|/2$, where $w_{c,t}$ and $w_{u,t}$ denote the $N_{c,t} \times 1$ and $N_{u,t} \times 1$ weight vectors of the conditional and unconditional portfolios, respectively. There is a greater composition change (from the unconditional strategy) in the low state. This result is consistent with Row 2–in the low state, the predictor takes more extreme values, which in turns makes the slope signal more important than the unconditional signal in the portfolio formation process.

Rows 4 to 7 show the out-of-sample difference in Information Ratio between the conditional and unconditional strategies, $IR_c - IR_u$, in each state (low and high). There is a clear relation between the level of the predictive signal (reported in Row 2) and the different performance measures. For every single predictor variable, the performance measures in the high state are higher than in the low state. Note that the high state in this context corresponds to months with a high difference between the conditional and unconditional signal and a low value of the predictor itself. Thus, the poor predictive signal of the single-predictor strategies is an indicator of lower performance.

The analysis in Table VIII also sheds light on the superior performance of the combination strategy. The combination strategy has a lower PSD (-1.6) in the low state than all other single predictor strategies whose PSD's range from -2.6 to-1.9. In the low state the value of the predictor (0.7) associated with the combination strategy is also lower than for the single predictors (which range from 0.8 to 1.0). Based on our reasoning above, we would therefore expect the combinations strategy to have a superior information ratio in the low states than all other single predictor strategies. As row 7 of Table VIII shows this is indeed the case. The combination strategy achieves an information ratio of 1.8 in the low state. Its information ratio in the high state (2.7) is about the same as that of the volatility predictor strategy (2.8). This suggests that the superior performance of the combination strategy comes from its performance in low state months. To summarize, the performance of the combination strategy can be traced back to a lower differential between the unconditional and conditional signal, a lower predictor value in the low state months and therefore less deviation from the unconditional portfolio. This interpretation is corroborated by the change in portfolio weights. The values for the combination strategy are 0.30 and 0.20 in the low and high state respectively and thus lower than all the other states.

Please insert Table VIII

B.3 Sensitivity Analysis

So far our results indicate that the combination strategy generates better risk-adjusted performance and a higher information ratios than all the other strategies. Our baseline result in Table VI are based on all funds and total return predictability. Is this result robust to alternative specifications? In Table IX we report a range of sensitivity checks. First we if we examine alpha instead of total return predictability our conclusions do not change qualitatively. The combination strategy still generates a higher information ratio (2.4) than the unconditional strategy (2.2). This is consistent with our discussion in Table II and III which showed that most in-sample total return predictability was driven by alpha predictability. One crucial constraint that any investor would face when attempting to rebalance a portfolio of hedge funds is that of notice periods. Notice periods imply that an investor that would like to redeem his investment in December would have to give notice to the fund several weeks in advance. Based on the average notice period across funds in our data, we therefore carry out a robustness check in which predictive regressions are estimated with data up to September of each year. Funds are rebalanced only in December based on the ranking produced in September. This is more consistent with portfolio rebalancing in practice. We find that taking into account notice periods in this way does not affect the finding that the combination strategy outperforms the unconditional strategy.

Our baseline results imposed a dynamic minimum Assets under Management (AuM) requirement that excludes small funds. Table IX shows that repeating our analysis with all funds still leads to an outperformance of the combination strategy, although the outperformance is lower than in the more realistic baseline case. Our conclusions are also unchanged by increasing the maximum number of funds in each strategies' portfolio from 100 to 200 or by requiring a minimum number of 60 observations. In both cases the combination strategy beats the unconditional strategy.

Please insert Table IX

So far we have documented that the combination strategy generates better risk-adjusted performance than the alternative strategies. Is this predictability driven by a particular group of hedge funds? To shed further light on the source and economic interpretation of predictability we report the baseline results by investment objective in Table X. We find that the combinations strategy performs particularly for the two largest hedge fund categories (Long/Short Equity and Funds of Funds). The superior performance of the combination strategy can therefore be traced back to this subgroup of funds.

Panel A reports results for Long/Short Equity Funds and shows that the combination strategy outperforms all other strategies with an Information Ratio of 1.3 and a p-value of 0.00. The next best strategy is the strategy based on the default spread that generates an Information Ratio of 1.3 and a p-value of 0.06. In terms of the Sharpe Ratio the combination strategy performs as well as the several of the other strategies but generates a statistically more significant Sharpe Ratio with a p-value of 0.02. For Market-Neutral funds the combinations strategy generates the highest Information Ratio after the single predictor strategy based on the dividend yield and the VIX, respectively. Panel C reports results for Managed Futures Funds and shows that the combination strategy only outperforms the multiple predictor and the single predictor (flows) strategy in terms of Sharpe Ratio. Similarly for Macro funds the combination strategy does not uniformly outperform (see Panel D). Panel E shows that the combination strategy is again useful in maximizing the performance of an portfolio of emerging markets funds. The combination strategy achieves the highest Information Ratio (0.7) and Sharpe Ratio (0.7). Similarly, the combination strategy dominates all other strategies in terms of Sharpe Ratio and Information Ratio when applied to convertible bond funds (Panel F). For Event Driven (Panel G) and Fixed Income (Panel H) funds the combination strategy does not generate the highest Information Ratio. For Fixed Income Funds the VIX and the Dividend Yield lead to the best risk-adjusted out-of-sample performance. Panels I and J show that for investors choosing among Funds of Funds and Multi-Strategy funds, respectively, the combination strategy adds value. For both categories the combination strategy generates the highest Information Ratio. For Multi-Strategy funds the VIX predictor strategy leads to an equally strong Information ratio and performs better in terms of Sharpe Ratio.

Please insert Table X

B.4 Impact of the 2008 Crisis

We have so far shown that the combination strategy leads to superior out-of-sample performance for a range of hedge fund categories during the 1994-2007 period. A natural additional out-of-sample test is to examine how the combination strategy performs during the 2008 hedge fund crisis. It is also of great practical importance for investors to know which strategy would have helped to best anticipate the events of 2008. Since our tests are constructed out-of-sample, our tests may identify a strategy that could have steered a portfolio of hedge funds clear of the hedge fund crisis of 2008 *without the benefit of hindsight*. As we noted above, we would not a priori expect the combination strategy to outperform the alternative strategies in any given year. Although the combination strategy is less affected by model uncertainty than alternative strategies, an individual predictor may play a more important role in any given year than the alternatives.

In Table XI we report the performance of the single predictor strategies and the combination strategy during 2008. In the first two columns of Table 10 we report the ex post excess return and Sharpe Ratio for different portfolios for the period 1994-2007. The combination strategy achieves the highest Sharpe Ratio (2.5) followed by the unconditional strategy (Sharpe Ratio of 2.3). Columns three and four show our the coefficients change as we add the year 2008 to the sample. The combination strategy's Sharpe Ratio falls by 0.7 to 1.8 for the period 1994-2008. The Sharpe Ratio of the VIX strategy falls from 2.0 to 1.8. while the unconditional strategy falls from 2.3 to 1.4. For comparison the Sharpe Ratio of the S&P500 falls from 0.4 to 0.1. When we examine the cumulative (geometric) return of the different strategies during the 2008 period we find that the combination strategy provides the third lowest return in both cases (dominated by the Dividend Yield and the VIX strategy).

To shed light on why different strategies perform well we also report the cross-sectional average of the unconditional alpha of funds in each portfolio in Column 8. One reason for the relatively strong performance of the VIX predictor strategy is that it selects funds with a high conditional mean on average (0.89). This is even high than for the combination strategy (0.84). Another instructive metric is provided by the statistic that captures when funds included in different strategies have the correct exposure to predictor variables. We calculate this statistic as in Table VII. For each month t, we measure the fund average slope coefficient for each portfolio: $\widehat{b}_{p,t} = \left((1/N_t)\sum_{i=1}^{N_t}\widehat{b}_{i,j}\right) I_{Z_{j,t}-\overline{Z}}$, where N_t is the number of funds included in the portfolio, $\widehat{b}_{i,j}$ is the fund estimated slope coefficient (over the previous three-year period), $I_{Z_{j,t}-\overline{Z}}$ is a function that take the value 1 if the predictor is above average and -1 otherwise. $\widehat{b}_{p,t}$ is positive only if the portfolio has the right exposure to the predictor j. Column 9 reports the cross-sectional average of the signed slope. It shows that one of the reasons why the VIX strategy performs well is that it has a positive sign of 0.16 on average so that most funds in this portfolio are correctly positioned. The default spread on the other hand has the wrong exposure (-0.52) given the predicted value and this goes some way towards explained its poor performance in 2008.[15] Similarly, the combination portfolio on the other hand has a cross-sectional average of -0.30 suggesting that many of the funds in the portfolio are not correctly positioned.

Please insert Table XI

The results in Panel A of Table XI are based on annual rebalancing which is likely to be realistic in practice. However, annual rebalancing does not allow the portfolios to quickly react to changes in predictor variables and predictor signals. Therefore in Panel B we examine the performance in 2008 of the different strategies when allowing for monthly rebalancing. Even if this may not be achievable in practice due to lockup and notice periods it is nevertheless instructive to examine the potential for superior performance due to more frequent rebalancing. As we would expect we find that all strategies would have generated superior and indeed uniformly *positive* performance during the fourth quarter of 2008 that marked the hedge fund crisis. The combination strategy would have achieved cumulative return of 3.4 in 2008 if monthly rebalancing was permitted. This compares with -15.8 (-37.8) percent in 2008 for a value-weighted portfolio of hedge funds (the S&P 500). Column 9 also again helps us shed light on why funds perform well when monthly rebalancing is allowed. Those strategies with a lower signed slope (0.13) such as the default spread also tend to produce a lower total return in 2008 (-0.5).

To better understand the performance of the combination strategy in 2008, we examine the cumulative return across hedge fund categories in Table XII. For Long/Short Equity Funds the lowest losses are achieved by the VIX predictor followed by Flows and the combination strategy. Overall the VIX seems to be the best predictor overall in terms of cumulative 2008 returns. It generates the best performance for Long/Short Equity Funds, Managed Futures Funds, Macro Funds, Emerging Markets Funds, Event-Driven Funds, Funds of Funds and Multi-Strategy Funds. The Second-best predictor is the dividend yield that leads to the highest cumulative return for categories Fixed Income and Market Neutral.

Please insert Table XII

[15] The signed slope for the aggregate flows predictor does not shed much light on the relatively low 2008 performance of the portfolio based on the fund flow predictor. This may be partly due to the fact that the signed slope is calculated based on 12 months of day and the fact that the aggregate flow predictor is the least persistent predictor in the sample.

V Conclusions

This paper develops and applies a framework in which to carefully assess the true forecasting power of economic variables in predictive regressions in a large universe of individual hedge funds. We shed light on the sources and economic interpretation of predictor models that generate superior out-of-sample performance. Specifically, we measure the proportions of hedge funds in the population having *truly* predictable returns with respect to any predictive variable. In addition, we examine whether predictability is due to time-varying alphas (i.e., managerial abilities), or to time-varying factor risk premia. Our econometric approach carefully accounts for "false discoveries", that is, funds that have a significant estimated exposure, $\widehat{b}$, to the predictor, while its true exposure is equal to zero ($b = 0$). We also carefully account for the small-sample bias by extending the bias-corrected approach of Amihud and Hurvich (2004). We carefully address issues related to illiquidity and show that our results are robust to alternative fund inclusion criteria as well as realistic portfolio rebalancing procedures and the use of lower frequency returns.

Using monthly returns for more than 15,000 funds during spanning the period January 1994 through December 2008, we find strong evidence of predictability in the hedge fund industry, in particular for the default spread, the VIX, and fund flows. Since hedge fund risk factor are nearly unpredictable during our sample period, we find that the bulk of return predictability is due to time-varying alphas. We show that the economic value of predictability can be improved by employing a strategy that combines forecasts from several single predictive regressions instead of relying on single or multiple predictive regressions. We extend the literature on mutual and hedge fund persistence by forming portfolios according to a time-varying performance metric–the fund conditional alpha t -statistics. This predictive signal, computed using a single predictor or all predictors simultaneously, automatically incorporates the signal of both the unconditional and time-varying alphas in one single measure. To account for specification uncertainty, we also implement a "combination" strategy which pools the conditioning information across the entire set of predictors, and across individual hedge funds.

Turning to the out-of-sample performance of the conditional hedge fund strategies, we find that the "combination" strategy which selects funds based on their conditional alpha t-statistic across all predictors, generates the highest risk-adjusted performance in 1994-2007 as well as 1994-2008, and consistently beats the unconditional strategy across all investment categories. The single-predictor strategies, which only use one single predictor at a time, are not able to outperform the unconditional strategy. We find that the conditional strategy which uses all predictors to predict fund alphas produces the lowest performance.We shed light on the source of this superior performance by showing that the combination strategy outperforms among the two largest hedge fund categories in our sample (Long/Short Equity and Funds of Funds). Finally, we use the financial crisis of 2008 as a natural out-of-sample test and show that the combination strategy produces superior risk-adjusted performance during the crisis.

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VI Appendix

A Measuring the Proportions of Unpredictable and Predictable Funds

We start with the estimation of the proportion $\pi_0(j)$ of unpredictable funds associated with predictor j $(j = 1, ..., J)$. Since these funds satisfy the null hypothesis $H_0 : b_{i,j} = 0$, their slope coefficient p-values are uniformly distributed over the interval $[0, 1]$ (see Barras, Scaillet, and Wermers (2009;BSW hereafter)). To recover this uniform distribution, we simply take a sufficiently high threshold λ^* beyond which the vast majority of p-values come from the unpredictable funds. After measuring the proportion $\widehat{w}(j, \lambda^*)$ of p-values above λ^*, we extrapolate it over the entire interval $[0, 1]$ by multiplying it by $1/(1 - \lambda^*)$:

$$\widehat{\pi}_0(j) = \widehat{w}(j, \lambda^*) \cdot (1 - \lambda^*)^{-1}. \tag{11}$$

To choose the optimal threshold λ^*,we use the bootstrap procedure proposed by Storey (2002) and Storey, Taylor, and Siegmund (2004).[16] This resampling approach consists in minimizing an estimate of the Mean-Squared Error (MSE) of $\widehat{\pi}_0(j, \lambda)$, defined as $E(\widehat{\pi}_0(j, \lambda) - \pi_0(j))^2$. First, we compute $\widehat{\pi}_0(j, \lambda)$ using Equation (11) across a range of λ values ($\lambda = 0.30, 0.35, ..., 0.70$). Second, for each possible value of λ, we form 1,000 bootstrap replications of $\widehat{\pi}_0(j, \lambda)$ by drawing with replacement from the $M \times 1$ vector of fund p-values. These are denoted by $\widehat{\pi}_0^b(\lambda)$, for $b = 1, ..., 1,000$. Third, we compute the estimated MSE for each possible value of λ:

$$\widehat{MSE}(j, \lambda) = \frac{1}{1,000} \sum_{b=1}^{1,000} \left[\widehat{\pi}_0^b(j, \lambda) - \min_{\lambda} \widehat{\pi}_0(j, \lambda) \right]^2. \tag{12}$$

We choose λ^* such that $\lambda^* = \arg\min_{\lambda} \widehat{MSE}(j, \lambda)$.

To estimate the proportions of predictable funds, $\pi_A^-(j)$ and $\pi_A^+(j)$, we use a similar approach which minimizes the estimated mean-squared error of their respective estimators. Based on Equation (4), we compute $\widehat{\pi}_A^-(\gamma)$ across a range of γ values ($\gamma = 0.30, 0.35, ..., 0.50$): $\widehat{\pi}_A^-(j) = \widehat{S}_\gamma^-(j) - \widehat{\pi}_0(j) \cdot \gamma/2$, where $\widehat{S}_\gamma^-(j)$ is the observed proportions of significant funds with negative estimated slope coefficient, $\widehat{b}_{i,j}$, (at the significance level γ), and $\widehat{\pi}_0(j)$ is the estimated proportion of unpredictable fund (from Equation (11)). Second, we form 1,000 bootstrap replications of $\widehat{\pi}_A^-(\gamma)$ for each possible value of γ. These are denoted by $\widehat{\pi}_A^{b-}(j, \gamma)$, for $b = 1, ..., 1,000$. Third, we compute the

[16] The main advantage of this procedure is that it is entirely data-driven. However, in a study on mutual fund performance, BSW find in that $\widehat{\pi}_0$ is not overly sensitive to the choice of λ^*. A simple approach which fixes the value of λ^* to intermediate levels (such as 0.5 or 0.6) produces similar estimates.

estimated MSE for each possible value of γ:

$$\widehat{MSE}^{-}(j,\gamma) = \frac{1}{1,000}\sum_{b=1}^{1,000}\left[\widehat{\pi}_A^{b-}(j,\gamma) - \max_{\gamma}\widehat{\pi}_A^{-}(j,\gamma)\right]^2. \quad (13)$$

We choose γ^- such that $\gamma^- = \arg\min_\gamma \widehat{MSE}^{-}(j,\gamma)$. We use the same data-driven procedure for $\widehat{\pi}_A^{+}(j,\gamma)$ to determine $\gamma^+ = \arg\min_\gamma \widehat{MSE}^{+}(j,\gamma)$. If $\min_\gamma \widehat{MSE}^{-}(j,\gamma) < \min_\gamma \widehat{MSE}^{+}(j,\gamma)$, we set $\widehat{\pi}_A^{-}(j) = \widehat{\pi}_A^{-}(\gamma^-)$. To preserve the equality $1 = \pi_0 + \pi_A^+ + \pi_A^-$, we set $\widehat{\pi}_A^{+}(j) = 1 - \widehat{\pi}_0 - \widehat{\pi}_A^{-}(j)$. Otherwise, we set $\widehat{\pi}_A^{+}(j) = \widehat{\pi}_A^{+}(\gamma^+)$ and $\widehat{\pi}_A^{-}(j) = 1 - \widehat{\pi}_0 - \widehat{\pi}_A^{+}(j)$.

B The Bias-Corrected Approach of Amihud and Hurvich (2004;AH)

B.1 Basic Framework

For each hedge fund i in the population $(i = 1, ..., M)$, we use the following predictive system:

$$\begin{aligned} r_{i,t+1} &= b_{i,0} + b_i' Z_t + u_{i,t+1}, \\ Z_{t+1} &= \theta + \Phi Z_t + \upsilon_{t+1}, \qquad t+1 = 1, ...T \end{aligned} \quad (14)$$

where $r_{i,t+1}$ the fund i excess return between t and $t+1$, Z_t is the $J \times 1$ vector of predictors observed at time t, $b_{i,0}$ is the intercept, $b_i = [b_{i,1}, ..., b_{i,J}]$ is the $J \times 1$ vector of slope coefficients, and Φ is the $J \times J$ companion matrix of the VAR(1). $u_{i,t+1}$ denotes the fund return innovation term, and υ_{t+1} is the $J \times 1$ predictor innovation vector. We assume that $u_{i,t+1} = E(u_{t+1} | \upsilon_{t+1}) + e_{i,t+1} = \phi_i' \upsilon_{t+1} + e_{i,t+1}$, where ϕ_i is the $J \times 1$ innovation coefficient vector, and $e_{i,t+1}$ is the residual term orthogonal to υ_{t+1}. While υ_{t+1} is modelled as an i.i.d. process, we allow $e_{i,t+1}$ to be autocorrelated (e.g., to account for the potential hedge fund illiquidity). Replacing $u_{i,t+1}$ in Equation (14), we obtain

$$r_{i,t+1} = b_{i,0} + b_i' Z_t + \phi_i' \upsilon_{t+1} + e_{i,t+1}. \quad (15)$$

By adding υ_{t+1} as an additional variable, the orthogonality condition holds (i.e., $E(e_{i,t+1} | Z_0, ..., Z_T, \upsilon_1, ..., \upsilon_{T+1}) = 0$), and the estimated coefficients, $\widehat{b}_{i,0}$, $\widehat{b}_i$, and $\widehat{\phi}_i$, are unbiased.[17] However, since υ_{t+1} is unobservable, the main issue is to find a proxy for υ_{t+1}, denoted by υ_{t+1}^c. The solution proposed by AH is to compute υ_{t+1}^c using the

[17] This is the main difference with the standard predictive regression in Equation (1), $r_{i,t+1} = b_{i,0} + b_i' Z_t + u_{i,t+1}$, where the orthogonality condition fails (i.e., $E(u_{i,t+1} | Z_0, ..., Z_T) \neq 0$).

bias-corrected estimates of the VAR system in Equation (14), $\widehat{\theta}^c$ and $\widehat{\Phi}^c$.

Starting with the estimation of $\widehat{\theta}^c$ and $\widehat{\Phi}^c$, we find, as in previous studies (e.g., Campbell (1991)), that there is weak evidence of cross-effects between our set of predictors.[18] Therefore, we pursue by assuming that the companion matrix Φ is diagonal, as suggested by AH.[19] We estimate the AR(1) model for each predictor j ($j = 1, ..., J$): $Z_{j,t+1} = \widehat{\theta}_j + \widehat{\rho}_j Z_{j,t} + \widehat{\upsilon}_{j,t+1}$. Then, each (unobservable) innovation term, $\upsilon_{j,t+1}$ is proxied with $\upsilon^c_{j,t+1} = Z_{j,t+1} - \widehat{\theta}^c_j - \widehat{\rho}^c_j Z_{j,t}$, where $\widehat{\rho}^c_j$ is the second-order bias corrected autocorrelation coefficient $\widehat{\rho}^c_j = \widehat{\rho}_j + (1+3\widehat{\rho}_j)/T_i + 3(1+3\widehat{\rho}_j)/T_i^2$, $\widehat{\theta}^c_j = \widehat{\theta}_j - (\widehat{\rho}^c_j - \widehat{\rho}_j)\overline{Z}_j$, T_i denotes the number of return observations, and $\overline{Z}_j$ is the predictor sample average. Finally, replacing $\upsilon_{j,t+1} = \upsilon^c_{j,t+1} + (\widehat{\theta}^c_j - \theta_j) + (\widehat{\rho}^c_j - \rho_j)Z_{j,t}$ into Equation (15), we have

$$r_{i,t+1} = b^c_{i,0} + \sum_{j=1}^{J} b^c_{i,j} Z_{j,t} + \sum_{j=1}^{J} \phi_{i,j} \upsilon^c_{j,t+1} + e_{i,t+1}, \tag{16}$$

where $b^c_{i,0} = b_{i,j} + \sum_{j=1}^{J} \phi_{i,j}(\widehat{\theta}^c_j - \theta_j)$ and $b^c_{i,j} = b_{i,j} + \phi_{i,j}\left(\widehat{\rho}^c_j - \rho_j\right)$. Based on a simple OLS estimation of Equation (16), we obtain the bias-corrected estimated slope coefficient, $\widehat{b}^c_{i,j}$, along with the estimated innovation coefficients, $\widehat{\phi}_{i,j}$ ($j = 1, ..., J$). While $\widehat{\phi}_{i,j}$ is unbiased (i.e., $E(\widehat{\phi}_{i,j}) = \phi_{i,j}$), AH show that the bias in $\widehat{b}^c_{i,j}$ does not completely disappear, because we use a proxy, instead of the (true) innovation vector υ_{t+1}. However, they show using a Monte-Carlo analysis that the magnitude of this remaining bias is very low. This result is confirmed by our own Monte-Carlo experiment, which is specifically designed to reproduce the salient features of hedge fund data (see Appendix C).

B.2 Extending the Approach to Alpha Predictability

While AH focus on return predictability, it is straightforward to extend their approach to examine alpha predictability. In this case, we simply add the risk factors to the set of explanatory variables in Equation (15):

$$r_{i,t+1} = a_{i,0} + a_i' Z_t + \phi_i' \upsilon_{t+1} + \beta_i' F_{t+1} + \epsilon_{i,t+1}, \tag{17}$$

[18] To be inserted some stats!...Among the 20 off-diagonal elements of $\widehat{\Phi}$, we find that only three of them are significantly different from zero at the 10% level. Using the Bonferroni threshold equal to 0.10/20 to account for multiple-testing, we find that none of them remain significant. , during our sample period 1994-2008,

[19] They show that when the (true) companion matrix Φ is diagonal and we fail to impose this condition on the estimated matrix $\widehat{\Phi}$, their approach leads to a much lower bias reduction in the estimated slope coefficients, $\widehat{b}_i$.

where F_{t+1} is the $K \times 1$ vector of portfolio-based factor excess returns, β_i denotes the $K \times 1$ vector of fund exposure to the K risk factors, and $\epsilon_{i,t+1}$ is the idiosyncratic term. Replacing υ_{t+1} with υ^c_{t+1} in Equation (17), we have:

$$r_{i,t+1} = a^c_{i,0} + \sum_{j=1}^{J} a^c_{i,j} Z_{j,t} + \beta^{c\prime}_i F_{t+1} + \sum_{j}^{J} \phi_{i,j} \upsilon^c_{j,t+1} + e_{i,t+1}, \tag{18}$$

where $a^c_{i,0} = a_{i,j} + \sum_{j=1}^{J} \phi_{i,j} (\widehat{\theta}^c_j - \theta_j) \overline{Z}_j$, and $a^c_{i,j} = a_{i,j} + \phi_{i,j} \left(\widehat{\rho}^c_j - \rho_j\right)$. Using the standard OLS estimation Equation (18), we obtain the bias-corrected estimated alpha slope coefficient, $\widehat{a}^c_{i,j}$, along with the estimated innovation coefficients, $\widehat{\phi}_{i,j}$ $(j = 1, ..., J)$. Note on Petkova innovation to proxy for the factors?

B.3 Estimating the Slope Coefficient t-statistic and p-value

Following AH, the estimated variance of fund i $(i = 1, ..., M)$ bias-corrected slope coefficient $\widehat{b}^c_{i,j}$ associated with predictor j $(j = 1, ..., J)$ equals

$$\widehat{var}(\widehat{b}^c_{i,j}) = \widehat{\phi}^2_{i,j} \widehat{var}(\widehat{\rho}^c_j) + \widehat{var}_{ols}(\widehat{b}^c_{i,j}), \tag{19}$$

where $\widehat{var}(\widehat{\rho}^c_j) = (1 + 3/T + 9/T^2)^2 \widehat{var}(\widehat{\rho}_j)$, and $\widehat{var}_{ols}(\widehat{b}^c_{i,j})$ is the $(j + 1)$ diagonal element of the $(2J + 1) \times (2J + 1)$ OLS estimated covariance matrix $\widehat{V}_{ols}(\widehat{b}^c_{i,0}, \widehat{b}^c_i, \widehat{\phi}_i)$ of the coefficients in Equation (16). $\widehat{V}_{ols}$ is equal to $(X'X)^{-1} \left(X' \widehat{V}_i X\right)^{-1} (X'X)^{-1}$, where $X = [x'_1, ..., x'_T]'$, $x_1 = [1, z'_1, \upsilon^{c\prime}_2]$, and $\widehat{V}_i$ is the $T \times T$ estimated covariance matrix of the residual vector $e_i = [e_{i,2}, ..., e_{i,T+1}]'$.

To estimate V_i, we determine the dependence structure in the fund residuals, $e_{i,t+1}$, based on an AR specification. Specifically, for each fund i, we compute the estimated innovations, $\widehat{e}_{i,t+1}$, based on Equation (16), and use them to obtain consistent estimators of the following AR(3) model: $e_{i,t+1} = \rho_{i,1} e_{i,t} + \rho_{i,2} e_{i,t-1} + \rho_{i,3} e_{i,t-2} + \xi_{i,t+1}$ (see Davidson and MacKinnon (2004), p. 277). Based on the p-values associated with the estimated coefficients, $\widehat{\rho}_{i,1}$, $\widehat{\rho}_{i,2}$, and $\widehat{\rho}_{i,3}$, we also determine the proportions of funds in the population which exhibit non-zero serial correlation at the three different lags using the same approach as the one outlined in Appendix A.

The results across the different investment categories are shown in Table XIII. The leftmost columns contain the cross-sectional median of the estimated first lag autocorrelation, $\widehat{\rho}_{i,1}$, along with its 25% and 75%-quantiles (in parentheses), as well as the estimated proportion of funds with non-zero first lag autocorrelation (i.e., funds with $\rho_{i,1} \neq 0$), and its associated standard deviation (in parentheses). The remaining columns repeat the analysis for the second and third lags.

Please insert Table AI

Starting with the analysis of the entire fund population, we see that 26.2% and 37.0% of the funds have a non-zero serial correlation at the first and second lags, respectively. On the contrary, only 2.1% of the funds have a third lag coefficient different from zero. This is confirmed by the estimated values, $\widehat{\rho}_{i,3}$, which are, for most funds, close to zero. The empirical findings remain qualitatively unchanged when we examine the different investment categories. Based on these results, we therefore model the dependence in the fund residual, $e_{i,t+1}$, using an AR(2).

Following Greene (1994, p. 544), we compute the estimated residual covariance matrix as $\widehat{V}_i = \widehat{var}(\widehat{\xi}_{i,t+1})\left(\widehat{\Psi}_i'\widehat{\Psi}_i\right)^{-1}$, where $\widehat{\Psi}_i$ is defined as

$$\widehat{\Psi}_i = \begin{bmatrix} \left(\frac{(1+\widehat{\rho}_{i,2})[(1-\widehat{\rho}_{i,2}^2)-\widehat{\rho}_{i,1}]}{1-\widehat{\rho}_{i,2}}\right)^{\frac{1}{2}} & 0 & 0 & 0 & ... & 0 & 0 & 0 \\ \frac{\widehat{\rho}_{i,1}(1-\widehat{\rho}_{i,1}^2)^{\frac{1}{2}}}{1-\widehat{\rho}_{i,2}} & (1-\widehat{\rho}_{i,2}^2)^{\frac{1}{2}} & 0 & 0 & ... & 0 & 0 & 0 \\ -\widehat{\rho}_{i,2} & -\widehat{\rho}_{i,1} & 1 & & ... & 0 & 0 & 0 \\ ... & ... & ... & ... & ... & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & ... & -\widehat{\rho}_{i,2} & -\widehat{\rho}_{i,1} & 1 \end{bmatrix} \quad (20)$$

The estimated t-statistic of the j^{th} bias-corrected slope coefficient is defined as $\widehat{t}\left(\widehat{b}_{i,j}^c\right) = \widehat{b}_{i,j}^c / \left(\widehat{var}(\widehat{b}_{i,j}^c)\right)^{\frac{1}{2}}$. The fund p-value used to compute the proportions of unpredictable and predictable funds (Appendix A) is computed as $\widehat{p}(\widehat{b}_{i,j}^c) = 2(1-F_N(\left|\widehat{t}(b_{i,j}^c)\right|))$, where F_N is the cumulative function of the t-statistic distribution with $T-(2J+1)$ degrees of freedom.

Finally, to compute the joint test of predictability using all predictors simultaneously, we use the Wald test suggested by Amihud, Hurvich, and Wang (2009): $\widehat{w}(\widehat{b}_i^c) = \widehat{b}_i^{c\prime}\widehat{V}\left(\widehat{b}_i^c\right)^{-1}\widehat{b}_i^c$, where $\widehat{V}\left(\widehat{b}_i^c\right)$ is the $J\times J$ estimated covariance matrix of the $J\times 1$ slope coefficient vector, $\widehat{b}_i^c$. While the diagonal elements of $\widehat{V}\left(\widehat{b}_i^c\right)$ are given by Equation (19), Amihud, Hurvich, and Wang (2009, p. 420) provide a similar expression for the covariance terms, $\widehat{cov}(\widehat{b}_{i,j}^c, \widehat{b}_{i,k}^c)$. The p-value associated with this joint test is computed as $\widehat{p}(\widehat{b}_i^c) = 1 - F_N(\widehat{w}(\widehat{b}_i^c))$, where F_N is the cumulative function of a χ^2 distribution with J degrees of freedom.

B.4 Estimating the Conditional Mean t-statistic

We start with the single-predictor case discussed in Section I.C. Using predictor j, we define the estimated conditional excess mean of fund i ($i = 1, ..., M$) over the riskfree rate between time t and $t+1$ as $\widehat{\mu}_{i,t} = \widehat{b}_{i,0}^c + \widehat{b}_{i,j}^c Z_{j,t}$, and its estimated variance as $\widehat{var}(\widehat{\mu}_{i,t}) = X_t' \widehat{V}\left(\widehat{b}_{i,0}^c, \widehat{b}_{i,j}^c\right) X_t$, where $X_t = [1, Z_{j,t}]'$ and $\widehat{V}\left(\widehat{b}_{i,0}^c, \widehat{b}_{i,j}^c\right)$ is the 2×2 estimated covariance matrix of $\widehat{b}_{i,0}^c$ and $\widehat{b}_{i,j}^c$. The estimated variance of the intercept $\widehat{b}_{i,0}^c$ is computed as

$$\widehat{var}(\widehat{b}_{i,0}^c) = \widehat{\phi}_{i,j}^2 \widehat{var}(\widehat{\theta}_j^c) + \widehat{var}_{ols}(\widehat{b}_{i,0}^c), \tag{21}$$

where $\widehat{var}(\widehat{\theta}_j^c) = \widehat{var}(\widehat{v}_j^c)/T_i + \overline{Z}_j^2 \widehat{var}(\widehat{\rho}_j^c)$, and $\widehat{var}_{ols}(\widehat{b}_{i,0}^c)$ is the upper-left element of $\widehat{V}_{ols}(\widehat{b}_{i,0}^c, \widehat{b}_i^c, \widehat{\phi}_i)$. The estimated covariance between $\widehat{b}_{i,0}^c$ and $\widehat{b}_{i,j}^c$ is given by

$$\widehat{cov}(\widehat{b}_{i,0}^c, \widehat{b}_{i,j}^c) = \widehat{\phi}_{i,j}^2 \widehat{cov}(\widehat{\theta}_j^c, \widehat{\rho}_j^c) + \widehat{cov}_{ols}(\widehat{b}_{i,0}^c, \widehat{b}_{i,j}^c), \tag{22}$$

where $\widehat{cov}(\widehat{\theta}_j^c, \widehat{\rho}_j^c) = -\overline{Z}_j \widehat{var}(\widehat{\rho}_j^c)$, and $\widehat{cov}_{ols}(\widehat{b}_{i,0}^c, \widehat{b}_{i,j}^c)$ is the second row-first column element of $\widehat{V}_{ols}(\widehat{b}_{i,0}^c, \widehat{b}_{i,j}^c, \widehat{\phi}_i)$. Finally, the estimated variance of the estimated slope coefficient $\widehat{b}_{i,j}^c$ is given by Equation (19). Using this result, we can compute the estimated t-statistic of the conditional alpha as $\widehat{t}\left(\widehat{\mu}_{i,t}\right) = \widehat{\mu}_{i,t} / \left(\widehat{var}(\widehat{\mu}_{i,t})\right)^{\frac{1}{2}}$.

In the multi-predictor case, computing the variance of the intercept and its covariance with the alpha slope coefficients is more complicated since $\widehat{b}_{i,0}^c$ is a function of all J predictor intercepts, i.e., $b_{i,0}^c = b_{i,0} + \sum_{j=1}^J \phi_{i,j}(\widehat{\theta}_j^c - \theta_j)$. However, the logic behind the approach remains unchanged.

B.5 Estimating the Slope Coefficient at the Quarterly Horizon

In Progress

C Monte-Carlo Analysis

In Progress

Table I
Descriptive Statistics

Panel A shows, for each investment category, the number of funds (in parentheses), as well as the fund cross-sectional median and the 25-75% quantiles (in parentheses) of the annualized excess mean over the riskfree rate (both excluding and including 2008), standard deviation, skewness and kurtosis. Panel B displays the (monthly) mean and standard deviation, first-order autocorrelation, and correlation matrix of the four variables used to predict fund returns. Panel C displays the (annualized) excess mean and standard deviation, as well as the correlation matrix of the Fung and Hsieh seven risk factors. All statistics are computed using monthly observations between January 1994 and December 2008.

Panel A Fund Excess Returns

	Mean (Ann.)	Mean (Ann.) includ. 2008	Std (Ann.)	Skewness	Kurtosis
Long-Short (3,007)	9.3 (5.0,14.2)	6.4 (2.4,11.3)	11.9 (8.4,16.6)	.09 (-.19,.38)	3.5 (2.8,4.4)
Mkt. Neutral (463)	5.2 (1.5,8.7)	4.2 (0.8,7.6)	7.6 (4.7,9.8)	.03 (-.31,.38)	3.6 (2.8,5.0)
Man. Fut. (1,174)	5.0 (0.7,9.9)	4.8 (0.7,9.4)	14.5 (9.2,20.2)	.25 (-.03,.54)	3.4 (2.8,4.4)
Macro (599)	6.7 (2.8,10.9)	5.5 (1.1,9.8)	12.1 (8.5,17.3)	.21 (-.09,.51)	3.5 (2.9,4.5)
Emerging (600)	11.4 (5.0,20.6)	7.2 (1.6,14.9)	16.9 (10.0,22.7)	-.03 (-.29,.22)	3.1 (2.5,4.2)
Convertible (279)	5.4 (2.9,7.8)	4.7 (1.6,6.9)	5.8 (3.8,8.8)	-.11 (-.69,.34)	4.4 (3.3,6.3)
Event-Driven (608)	7.6 (4.6,11.2)	5.8 (2.5,9.8)	7.3 (4.6,11.0)	.02 (-.50,.40)	4.6 (3.4,6.3)
Fixed Income (673)	5.1 (2.2,8.6)	3.6 (0.0,7.0)	6.1 (3.8,8.9)	-.04 (-.81,.42)	4.4 (3.3,7.7)
F. of Funds (3,611)	5.8 (3.5,8.9)	2.2 (-0.3,4.8)	7.3 (4.3,9.3)	-.09 (-.55,.23)	3.4 (2.8,4.8)
Multi-Strat. (1.883)	7.0 (3.9,11.0)	6.3 (3.1,10.5)	9.0 (5.4,14.2)	.11 (-.25,.41)	3.2 (2.7,4.6)
All Funds (15,922)	6.9 (3.4,11.2)	4.7 (1.1,9.0)	9.4 (6.0,14.9)	.06 (-.32,.38)	3.5 (2.8,4.8)

Panel B Predictors

				Correlation matrix		
	Mean (Mon.)	Std. (Mon.)	Autocorr	Dividend	Volatility	Agg. Flow
Default spread	0.8	0.2	0.95	-.26	.30	.07
Dividend yield	2.0	0.4	0.97		-.48	.01
Volatility (VIX)	19.5	6.7	0.43			-.07
Aggregate Flow	0.9	1.8	0.25			

Panel C Risk Factors

					Correlation matrix			
	Mean (Ann.)	Std.(Ann.)	Size	Term	Def.	T. Bond	T. Cur.	T. Com.
Equity Market	7.2	13.9	-.06	-.11	.30	-.14	-.12	-.09
Equity Size	-2.7	13.1		-.15	.20	-.05	.02	-.02
Bond Term	2.4	7.1			-.33	.06	.14	.08
Bond Default	2.2	4.1				-.12	-.15	-.12
Trend Bond	-17.2	51.6					.16	.16
Trend Currency	-3.6	64.8						.26
Trend Commodity	-8.8	46.1						

Table II

Individual Fund Predictability

Panel A measures the predictive ability of the four variables (Default spread, Dividend yield, Volatility, and Aggregate flow) on individual fund excess returns (over the riskfree rate). For each investment category, we report the cross-sectional median and 25-75% quantiles (in parentheses) of the estimated slope coefficient, $\widehat{b}_j$, associated with predictor j ($j = 1, ..., 4$). Each coefficient is standardized (by multiplying the initial estimate by the predictor standard deviation) so that it corresponds to the change in the fund monthly excess return for a one standard deviation increase in the predictor value. We also report the proportion of predictable funds in the population having a negative and a positive relation with predictor j, $\widehat{\pi}_A^-(b_j)$ and $\widehat{\pi}_A^+(b_j)$ (associated standard deviation shown in parentheses). The final column (Joint) shows the estimated proportion of predictable funds in the population using all predictors simultaneously. In Panel B, we use the same procedure to measure individual fund alpha predictability. The estimated slope coefficients (for both return and alpha) and associated p-values are obtained from a multiple regressions after applying the bias-corrected approach explained in the appendix. They are computed using monthly data between January 1994 and December 2007.

Panel A Excess Return Predictability

	Default spread			Dividend yield			Volatility (VIX)			Aggregate flow			Joint
	Coefficient	Proportion		Coefficient	Proportion		Coefficient	Proportion		Coefficient	Proportion		
		−	+		−	+		−	+		−	+	Prop.
Long-Short	.17(-.20,.58)	4.6	27.2	-.16(-.54,.22)	23.7	3.6	-.23(-.70,.17)	30.4	2.1	-.35(-.73,-.07)	41.9	0.0	69.7
Mkt. Neutral	.02(-.20,.25)	8.9	13.4	-.15(-.40,.08)	32.9	1.2	-.03(-.34,.25)	17.7	12.9	-.11(-.33,.07)	28.6	0.4	68.6
Man. Future	-.01(-.32,.32)	7.8	7.6	.04(-.35,.59)	10.0	19.9	.26(-.09,.78)	0.0	26.6	-.06(-.41,.23)	11.0	2.7	48.9
Macro	.13(-.17,.49)	0.0	22.1	-.16(-.55,.21)	23.0	4.4	.10(-.32,.46)	8.8	20.2	-.14(-.53,.13)	22.4	0.0	53.2
Emerging	.60(.13,1.05)	0.0	51.1	-.14(-.60,.31)	19.6	7.8	-.45(-1.13,.11)	40.5	4.2	-.48(-.99,-.15)	52.5	0.0	70.0
Convertible	.16(-.02,.40)	0.0	37.4	-.06(-.31,.08)	15.5	0.0	-.08(-.29,.17)	28.6	15.8	-.21(-.37,-.06)	53.1	0.0	84.2
Event-Driven	.12(-.14,.35)	7.8	30.8	-.09(-.31,.10)	15.2	0.0	-.20(-.47,.04)	41.1	1.2	-.15(-.40,.00)	34.9	0.0	65.3
Fixed Income	.08(-.07,.33)	1.5	26.6	-.09(-.33,.08)	24.9	1.1	.02(-.27,.26)	15.8	18.9	-.05(-.23,.10)	14.1	0.0	58.2
F. of Funds	.23(.07,.44)	0.0	44.5	-.19(-.44,.00)	36.0	0.0	-.16(-.38,.09)	35.4	0.0	-.23(-.43,-.09)	47.7	0.0	74.0
Multi-Strategy	.18(-.04,.44)	0.0	30.8	-.13(-.40,.14)	26.2	4.1	.00(-.30,.35)	18.1	13.3	-.23(-.52,-.04)	36.7	0.0	68.7
All Funds	.16(-.10,.46)	1.0	30.7	-.12(-.44,.16)	25.2	4.2	-.10(-.44,.25)	25.9	8.6	-.22(-.52,.00)	35.9	0.0	66.8

Table II

Individual Fund Predictability (Continued)

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Panel B Alpha Predictability

	Default spread			Dividend yield			Volatility (VIX)			Aggregate flow			Joint
	Coefficient	Proportion		Coefficient	Proportion		Coefficient	Proportion		Coefficient	Proportion		
		−	+		−	+		−	+		−	+	Prop.
Long-Short	.13(-.20,.52)	4.3	24.2	-.26(-.68,.10)	26.6	0.0	-.18(-.62,.20)	26.7	3.2	-.21(-.51,.06)	29.1	0.0	59.9
Mkt. Neutral	.01(-.23,.21)	9.5	13.7	-.12(-.39,.11)	22.2	0.0	-.03(-.32,.23)	17.0	11.2	-.08(-.30,.11)	23.8	3.7	57.9
Man. Future	.00(-.40,.31)	11.8	7.0	.09(-.34,.61)	5.8	15.7	.19(-.20,.63)	0.0	18.0	-.13(-.52,.16)	25.0	4.0	47.4
Macro	.10(-.21,.46)	1.3	17.1	-.17(-.59,.22)	25.7	4.2	.01(-.41,.41)	10.0	15.8	-.10(-.41,.16)	18.1	0.5	51.8
Emerging	.55(.09,1.07)	0.0	47.6	-.30(-.83,.13)	29.7	0.3	-.45(-1.20,.14)	39.3	4.7	-.26(-.63,.03)	18.1	0.0	62.9
Convertible	.10(-.07,.35)	0.2	30.5	-.07(-.37,.07)	14.5	0.0	-.02(-.25,.26)	16.6	22.2	-.15(-.31,.00)	45.9	1.5	78.5
Event-Driven	.06(-.16,.27)	10.5	19.7	-.11(-.40,.07)	22.3	0.0	-.14(-.39,.10)	31.5	4.3	-.09(-.26,.07)	21.0	0.0	51.0
Fixed Income	.08(-.09,.30)	3.7	23.7	-.10(-.36,.10)	24.9	0.5	.01(-.26,.25)	15.8	18.4	-.00(-.18,.13)	11.2	1.7	59.4
F. of Funds	.19(.02,.39)	0.0	31.3	-.22(-.49,-.03)	37.4	0.0	-.16(-.36,.03)	25.6	0.0	-.17(-.34,-.04)	37.9	0.0	65.2
Multi-Strategy	.16(-.08,.42)	0.0	31.5	-.17(-.50,.10)	30.9	1.0	-.04(-.31,.27)	14.7	6.5	-.21(-.48,-.02)	40.4	0.0	64.8
All Funds	.12(-.12,.42)	2.1	26.0	-.16(-.52,.11)	28.2	0.3	-.10(-.41,.22)	23.3	5.6	-.16(-.41,.05)	29.6	0.5	59.6

Table III
Return Versus Alpha Predictability

Panel A measures the predictive ability of the four variables (Default spread, Dividend yield, Volatility, and Aggregate flow) on the Fung-Hsieh seven risk factors. The estimated slope coefficients and associated p-values (in parentheses) are obtained from a multiple regression after applying the bias-corrected approach explained in the appendix. The final column contains the p-value of joint significance using all four predictors. The leftmost columns in Panel B shows, for each investment category, the cross-fund median exposure (beta) to the Fung-Hsieh risk factors. The rightmost columns reports for each predictor the cross-fund median of the difference between return and alpha estimated slope coefficients, $(abs(\widehat{b}_i - (\widehat{a}_i)$, as a percentage of the median estimated alpha slope coefficient. The results are based on monthly data between January 1994 and December 2007.

Panel A Risk Factor Predictability

	Default	Dividend	Volatility	Flow	Joint p-val.
Equity Market	-.34 (.01)	.24 (0.49)	.13 (.39)	-.27 (.03)	.01
Equity Size	.40 (.19)	-.35 (.30)	-.49 (.16)	-.57 (.04)	.10
Bond Term	-.12 (.39)	.07 (.67)	.28 (.11)	.18 (.25)	.43
Bond Default	.25 (.00)	.03 (.77)	-.16 (.08)	-.03 (.73)	.04
Trend Bond	-1.63 (.11)	2.67 (.02)	5.87 (.00)	.78 (.44)	.00
Trend Curren.	1.32 (.36)	-.60 (.70)	-.40 (.81)	.13 (.93)	.88
Trend Commo.	-.71 (.44)	-1.19 (.24)	-.27 (.79)	1.13 (.25)	.53

Panel B Fund Exposure to Systematic Risk

	Exposure to FH factors							Alpha vs Sytematic Risk (%)			
	Mark.	Size	Term	Def.	T.B.	T.Cu.	T.Co.	Def.	Div.	Vol.	Flow
Long-Short	.30	.15	.01	.12	.00	.01	.01	39.2	55.4	46.3	51.0
Mkt. Neutral	.04	.02	.03	.07	.00	.01	.00	38.0	62.4	39.8	42.3
Man. Future	.03	.02	.11	.06	.02	.03	.01	48.4	44.6	67.9	52.2
Macro	.10	.05	.09	.13	.01	.02	.01	51.6	45.9	60.3	53.2
Emerging	.42	.15	.01	.45	.00	.01	.01	24.2	51.6	33.7	49.4
Convertible	.02	.04	.01	.18	.00	.00	.00	40.9	49.9	43.3	23.8
Event-Driven	.14	.10	.01	.23	.00	.00	.00	48.9	46.0	51.2	48.7
Fixed Income	.04	.01	.04	.18	.00	.00	.00	39.0	37.2	43.3	40.6
F. of Funds	.15	.05	.02	.18	.00	.01	.01	34.8	35.6	53.1	37.2
Multi-Strategy	.12	.06	.06	.12	.00	.00	.01	34.0	42.2	53.4	38.9
All Funds	.15	.07	.03	.15	.00	.00	.01	39.5	45.0	51.6	46.8

Table IV

Individual Fund Return Predictability at the Quarterly Horizon

We measure the predictive ability of the four variables (Default spread, Dividend yield, Volatility, and Aggregate flow) on individual fund quarterly excess returns (over the riskfree rate). For each investment category, we report the cross-sectional median and 25-75% quantiles (in parentheses) of the estimated slope coefficient, $\widehat{b}_j$, associated with each predictor. Each coefficient is divided by 3 and standardized (by multiplying the initial estimate by the predictor standard deviation) so that it corresponds to the change in the fund monthly excess return (over the next quarter) for a one standard deviation increase in the predictor value. The estimated slope coefficients and associated p-values are obtained from a multiple regressions using overlapping return observations after applying the bias-corrected approach explained in the appendix. They are computed using monthly overlapping returns between January 1994 and December 2007.

	Default spread	Dividend yield	Volatility (VIX)	Aggregate flow
Long-Short	.14 (-.25,.56)	-.04(-.40,.40)	-.08 (-.49,.31)	-.22 (-.50,.02)
Mkt. Neutral	.02 (-.26,.24)	-.10 (-.30,.12)	.01 (-.25,.28)	-.07 (-.23,.10)
Man. Future	.04 (-.29,.43)	.03 (-.36,.50)	.21 (-.13,.61)	-.02 (-.27,.23)
Macro	.14 (-.21,.55)	-.09 (-.45,.26)	.07 (-.31,.41)	-.06 (-.30,.16)
Emerging	.53 (.05,1.03)	-.07 (-.28,.51)	-.21 (-0.73,.21)	-.31 (-.72,-.05)
Convertible	.11 (-.04,.37)	.02 (-.26,.21)	.05 (-.21,.29)	-.16 (-.30,-.02)
Event-Driven	.07 (-.16,.30)	-.01 (-.20,.19)	-.05 (-.30,.19)	-.12 (-.28,.03)
Fixed Income	.07 (-.11,.32)	-.03 (-.24,.17)	.03 (-.22,.31)	.00 (-.16,.15)
F. of Funds	.23 (.03,.49)	-.03 (-.21,.11)	-.09 (-.29,.10)	-.14 (-.27,-.01)
Multi-Strategy	.19 (-.06,.50)	-.01 (-.24,.21)	.02 (-.21,.34)	-.13 (-.33,-.06)
All Funds	.15 (-.12,.49)	-.02 (-.29,.24)	-.03 (-.32,.30)	-.13 (-.34,.06)

Table V

Price Reaction to Unexpected Changes in Predictor Values

We measure the contemporaneous hedge fund price reaction to unexpected changes in the four predictive variables (Default spread, Dividend yield, Volatility, and Aggregate flow). For each investment category, we report the cross-sectional median and 25-75% quantiles (in parentheses) of the estimated innovation coefficient, $\widehat{\phi}_j$, associated with predictor j ($j = 1, ..., 4$). Each coefficient is standardized (by multiplying the initial estimate by the predictor standard deviation) so that it corresponds to the hedge fund price reaction to a one standard deviation change in the predictor value. We also report the proportion of funds exhibiting a negative and a positive price reaction to predictor j, $\widehat{\pi}_A^-(\phi_j)$ and $\widehat{\pi}_A^+(\phi_j)$ (associated standard deviation shown in parentheses). The final column (Joint) shows the estimated proportion of funds in the population exhibiting a price reaction using all predictors simultaneously. The estimated innovation coefficients and associated p-values are obtained from a multiple regression after applying the bias-corrected approach explained in the appendix. They are computed using monthly data between January 1994 and December 2007.

	Default spread			Dividend yield			Volatility (VIX)			Aggregate flow			Joint
	Coefficient	Prop.		Coefficient	Prop.		Coefficient	Prop.		Coefficient	Prop.		
		−	+		−	+		−	+		−	+	Prop.
Long-Short	-.53(-1.29,.11)	25.9	0.0	-1.99(-4.38,-.79)	74.8	0.0	-.21(-.92,.49)	24.7	9.1	-.24(-.68,.13)	31.8	1.2	89.7
Mkt. Neutral	-.36(-.87,.17)	38.7	5.2	-0.60(-1.47,.07)	49.6	7.7	.16(-.26,.78)	10.0	29.1	-.01(-.20,.26)	8.2	5.1	76.8
Man. Future	-.30(-1.20,.36)	8.3	0.0	-.10(-1.39,1.72)	18.3	12.7	.29(-.33,1.13)	1.7	24.4	-.44(-1.00,.05)	39.2	0.0	67.6
Macro	-.29(-1.05,.32)	17.6	0.0	-.99(-2.44,.17)	47.8	3.5	.12(-.57,.82)	9.8	19.4	-.33(-.77,.06)	30.9	0.0	72.2
Emerging	-.84(-1.88,.04)	30.5	0.0	-3.47(-8.21,-1.32)	83.3	0.0	-.44(-1.10,.18)	24.8	0.0	-.38(-.94,-01)	35.7	0.0	91.8
Convertible	-.38(-.86,-.08)	39.1	0.0	-.66(-1.90,-.14)	58.2	0.0	.06(-.23,.31)	8.8	24.6	-.07(-.20,.08)	25.1	0.8	79.3
Event-Driven	-.50(-1.08,-.08)	41.4	0.0	-1.38(-2.85,-.57)	76.0	0.0	-.32(-.69,.06)	42.7	4.6	-.07(-.27,.14)	25.2	4.7	92.6
Fixed Income	-.37(-.85,.01)	41.1	0.0	-.46(-1.37,-.07)	45.0	0.0	.09(-.29,.61)	15.0	31.5	-.02(-.20,.17)	14.1	2.7	79.2
F. of Funds	-.55(-1.00,-.21)	52.8	0.0	-1.17(-1.87,-.68)	89.0	0.0	-.05(-.37,.67)	23.7	19.0	-.15(-.39,.09)	40.8	4.0	96.3
Multi-Strategy	-.69(-1.49,-.23)	47.6	0.0	-.98(-1.95,-.24)	63.7	5.2	.13(-.27,.93)	11.1	25.6	-.17(-.56,.12)	38.8	4.8	89.1
All Funds	-.51(-1.16,-.01)	33.7	0.2	-1.19(-2.60,-.34)	66.0	2.7	-.04(-.56,.64)	20.4	16.5	-.18(-.58,.10)	35.2	1.8	86.7

Table VI
Economic Value of Predictability

In Panel A, we measure the out-of-sample performance of decile portfolios which select the 10% of funds with the highest conditional mean predictive signal. While the single-predictor strategies only use one of the four predictors (Default spread, Dividend yield, Volatility, and Aggregate flow), the "All predictors" strategy uses all of them simultaneously to compute the fund predictive signal. The combination strategy computes the predictive signal by averaging across the single-predictor signals. We report the annualized excess mean ($\widehat{\mu}$), standard deviation ($\widehat{\sigma}_{tot}$), Sharpe ratio (SR), Fung-Hsieh alpha ($\widehat{\alpha}$), residual standard deviation ($\widehat{\sigma}_{res}$), Information ratio (IR), as well as the 5-95% quantiles of the monthly excess return distribution. In parentheses are the one-sided p-values indicating whether the conditional strategy outperforms the unconditional strategy that ranks funds based on their unconditional signals only. All portfolios are formed at the end of the year, and rebalanced annually. The initial formation date is on December 31, 1996, and the final one on December 31, 2007. For comparison purposes, we also report the performance of hedge fund value-weighted (VW) and equally-weighted (EW) indices, as well as the SP500. For each strategy, Panel B shows the annual turnover, along with the portfolio exposure (beta) to the Fung-Hsieh seven risk factors.

Panel A Portfolio Performance

	Return (Ann.)			Fung-Hsieh Alpha (Ann.)			Quantiles	
Nb. funds: 94	$\widehat{\mu}$	$\widehat{\sigma}_{tot}$	SR	$\widehat{\alpha}$	$\widehat{\sigma}_{res}$	IR	5%	95%
Uncond.	5.8	4.1	1.4	5.4	2.6	2.1	-1.6	1.6
Single-Predic.								
Default Spread	6.8(.12)	5.7	1.2(.83)	6.4(.14)	3.9	1.6(.88)	-2.4	2.2
Dividend Yield	7.0(.04)	4.9	1.4(.39)	6.3(.10)	3.3	1.9(.56)	-1.5	2.4
Volatility (VIX)	7.7(.01)	4.2	1.8(.10)	7.1(.01)	3.5	2.0(.43)	-1.4	2.3
Aggregate Flow	6.9(.09)	4.2	1.6(.12)	6.8(.04)	3.2	2.1(.48)	-1.6	2.3
Multiple-Predic.								
All predictors	5.9(.41)	4.6	1.3(.54)	5.3(.52)	3.9	1.4(.90)	-2.2	3.1
Combination	7.1(.01)	4.0	1.8(.00)	6.8(.00)	2.7	2.5(.03)	-1.5	2.0
VW Index	3.7	5.7	0.6	2.8	4.1	0.7	-2.5	3.1
EW Index	4.4	5.7	0.8	3.6	3.8	0.9	-2.2	2.8
SP500	1.2	15.9	0.1	na	na	na	-8.7	6.4

Panel B Portfolio Characteristics

		Exposure to the Fung-Hiesh Risk Factors						
	Turnover	Mark.	Size	Term	Def.	T.Bond	T.Cu.	T.Co.
Unconditional	56.3	.12	.07	.04	.20	-.01	.00	.00
Single-Predic.								
Default Spread	73.5	.17	.08	.05	.23	-.01	.00	-.01
Dividend Yield	66.8	.17	.13	.10	.10	-.01	.00	.00
Volatility (VIX)	66.9	.11	.07	.06	.10	-.01	.00	.00
Aggregate Flow	62.1	.09	.08	.00	.18	-.01	.00	.00
Multiple-Predic.								
All predictors	89.6	.14	.09	.06	.04	-.01	.01	.01
Combination	58.7	.11	.07	.03	.14	-.01	.00	.00

Table VII

Performance Using Slope Signal Only

We measure the out-of-sample performance of decile portfolios which select the 10% of funds with the highest slope signal associated with each of the four predictors (Default spread, Dividend yield, Volatility, and Aggregate flow), The combination strategy computes the slope signal by averaging across the single-predictor signals. We report the annualized excess mean ($\widehat{\mu}$), standard deviation ($\widehat{\sigma}_{tot}$), Sharpe ratio (SR), Fung-Hsieh alpha ($\widehat{\alpha}$), residual standard deviation ($\widehat{\sigma}_{res}$), Information ratio (IR), as well as the 5-95% quantiles of the monthly excess return distribution. In parentheses are the one-sided p-values indicating whether the slope signal strategy outperforms the predictive signal strategy that ranks funds based on their predictive signals (see Table VI). All portfolios are formed at the end of the year, and rebalanced annually. The initial formation date is on December 31, 1996, and the final one on December 31, 2007. The rightmost columns report the difference between the average unconditional mean and slope coefficient of the funds included in the "slope signal" and "predictive signal" portfolios, respectively.

	Return (Ann.)		FH Alpha (Ann.)		Slope vs Predictive signals Fund average difference	
	$\widehat{\mu}$	SR	$\widehat{\alpha}$	IR	uncond. mean	slope coeff.
Single-Predic.						
Default Spread	6.6(.53)	0.9(.91)	6.1(.54)	1.1(.94)	-.36	-.05
Dividend Yield	6.7(.57)	0.8(.99)	5.0(.84)	0.8(1.00)	-.28	.30
Volatility (VIX)	6.3(.82)	0.9(.96)	5.3(.86)	0.8(1.00)	-.43	.30
Aggregate Flow	0.8(.98)	0.1(.99)	1.1(.99)	0.2(1.00)	-.49	-.14
Multiple-Predic.						
Combination	5.7(.72)	0.8(.97)	5.2(.77)	0.9(1.00)	-.40	.06

Table VIII
Signal Quality and Portfolio Performance

For each single-predictor strategy (Default spread, Dividend yield, Volatility, Aggregate flow), we compute its monthly predictive signal differential (against the unconditional predictive signal), and form two groups of months according to the signal level: Low (L), and High (H). In each state (L, H), we compute the average predictor absolute value, the change in the portfolio composition (against the unconditional strategy), as well as the annualized excess mean, Sharpe ratio, Fung-Hsieh alpha, and Information ratio. The predictor is standardized so that a value of 1 indicates that the original predictor value is one standard deviation above (below) its average. For the combination strategy, we use a similar approach where the monthly predictive signal and predictor value correspond to the simple averages of the single-predictor signals and predictor values, respectively. Each column "Diff" reports the difference between the High and the Low states.

	Default spread		Dividend yield		Volatility (VIX)		Aggregate flow		Combination	
	L/H	Diff	L/H	Diff	L/H	Diff	L/H	Diff	L/H	Diff
Predict. signal	-2.6/0.0	2.6	-1.9/0.2	2.1	-2.2/-0.1	2.1	-1.9/-0.2	1.7	-1.6/0.2	1.8
(vs Uncond.)										
Predict. value	0.9/0.4	-0.5	0.9/0.5	-0.4	0.8/0.6	-0.2	1.0/0.5	-0.5	0.7/0.6	-0.1
Port. weight	.54/.33	-.21	.48/.33	-.14	.45/.32	-.13	.35/.31	-.4	.30/.20	-.10
(vs Uncond.)										
Performance										
Excess mean	5.6/8.0	2.4	4.1/10.0	5.9	5.6/9.8	4.2	4.7/9.1	4.4	5.0/9.2	4.2
Sharpe ratio	0.8/2.2	1.4	0.7/2.4	1.7	1.2/2.6	1.4	1.0/2.2	1.2	1.1/2.7	1.6
FH Alpha	5.3/7.7	2.4	4.5/8.2	3.6	5.9/8.6	2.7	5.2/8.4	3.3	5.8/8.0	2.2
Info. Ratio	1.0/2.4	1.4	1.1/2.4	1.3	1.4/2.8	1.4	1.5/2.5	1.0	1.8/2.7	0.9

Table IX
Sensitivity Analysis

We compare the out-of-sample performance of the combination and the unconditional strategies for different specifications. "Alpha Predictability" selects funds based on their alpha signals (as opposed to their excess mean signals). "Notice Period" incorporates a three-month notice period before rebalancing the portfolios (i.e., decisions are taken at the end of September instead of December). "No AUM Limit" does not exclude the smallest funds from the sample. "Limit: 200 Funds" increases the upper limit of funds to be included in the portfolios from 100 to 200. Finally, "Estimation: 60 Obs." requires a minimum of 60 monthly return observation (after the first five years) to estimate the fund signals. For each specification, we report the annualized excess mean ($\widehat{\mu}$), standard deviation ($\widehat{\sigma}_{tot}$), Sharpe ratio (SR), Fung-Hsieh alpha ($\widehat{\alpha}$), residual standard deviation ($\widehat{\sigma}_{res}$), Information ratio (IR), as well as the 5-95% quantiles of the monthly excess return distribution. In parentheses are the one-sided p-values indicating whether the conditional strategy outperforms the unconditional strategy. All portfolios are formed at the end of the year, and rebalanced annually. Except for "Notice Period", the initial formation date is on December 31, 1996, and the final one on December 31, 2007.

	Return (Ann.)			Fung-Hsieh Alpha (Ann.)			Quantiles	
	$\widehat{\mu}$	$\widehat{\sigma}_{tot}$	SR	$\widehat{\alpha}$	$\widehat{\sigma}_{res}$	IR	5%	95%
Alpha Predictability								
Unconditional	5.8	3.6	1.6	5.5	2.5	2.2	-1.6	1.6
Combination	6.7(.02)	3.8	1.8(.18)	6.5(.00)	2.7	2.4(.09)	-1.5	2.0
Notice Period								
Unconditional	5.1	4.4	1.2	4.5	2.9	1.6	-1.6	2.0
Combination	5.1(.47)	3.2	1.6(.06)	4.7(.34)	2.3	2.0(.08)	-1.3	1.7
No AUM Limit								
Unconditional	6.9	3.1	2.2	6.7	2.3	2.9	-1.0	1.5
Combination	8.0(.02)	3.5	2.3(.10)	7.7(.03)	2.4	3.1(.07)	-1.1	2.0
Limit: 200 Funds								
Unconditional	5.4	4.8	1.1	4.8	3.2	1.5	-2.3	2.1
Combination	6.9(.00)	4.8	1.4(.00)	6.4(.00)	3.2	2.0(.00)	-1.4	2.3
Estimation: 60 Obs.								
Unconditional	4.4	5.1	0.8	3.7	3.5	1.0	-1.8	2.4
Combination	5.8(.04)	5.6	1.0(.06)	5.1(.03)	3.9	1.3(0.9)	-2.0	2.7

Table X

Economic Value of Predictability across Investment Categories

For each investment category (Panels A to J), we measure the out-of-sample performance of the unconditional, single-predictor, "All predictors" and combination strategies. We report the annualized excess mean ($\widehat{\mu}$), standard deviation ($\widehat{\sigma}_{tot}$), Sharpe ratio (SR), Fung-Hsieh alpha ($\widehat{\alpha}$), residual standard deviation ($\widehat{\sigma}_{res}$), Information ratio (IR), as well as the 5-95% quantiles of the monthly excess return distribution. In parentheses are the one-sided p-values indicating whether the conditional strategy outperforms the unconditional strategy. All portfolios are formed at the end of the year, and rebalanced annually. The initial formation date is on December 31, 1996, and the final one on December 31, 2007.

Panel A Long-Short

	Return (Ann.)			Fung-Hsieh Alpha (Ann.)			Quantiles	
Nb. funds: 39	$\widehat{\mu}$	$\widehat{\sigma}_{tot}$	SR	$\widehat{\alpha}$	$\widehat{\sigma}_{res}$	IR	5%	95%
Uncond.	6.1	8.1	0.8	5.2	5.2	1.0	-3.8	4.1
Single-Predic.								
Default Spread	9.0(.02)	9.7	1.0(.06)	8.2(.02)	6.4	1.3(.06)	-3.9	4.8
Dividend Yield	9.1(.00)	9.3	1.0(.09)	7.8(.02)	6.3	1.2(.13)	-3.7	4.7
Volatility (VIX)	7.5(.06)	7.6	1.0(.03)	6.8(.00)	5.6	1.2(.05)	-3.2	4.0
Aggregate Flow	6.5(.39)	8.3	0.8(.44)	5.8(.31)	5.9	1.0(.50)	-3.4	3.8
Multiple-Predic.								
All predictors	6.7(.37)	8.3	0.8(.41)	6.7(.17)	5.4	1.2(.22)	-3.6	4.4
Combination	8.5(.00)	8.7	1.0(.02)	7.6(.00)	5.6	1.3(.00)	-3.2	4.5

Panel B Market Neutral

	Return (Ann.)			Fung-Hsieh Alpha (Ann.)			Quantiles	
Nb. funds: 20	$\widehat{\mu}$	$\widehat{\sigma}_{tot}$	SR	$\widehat{\alpha}$	$\widehat{\sigma}_{res}$	IR	5%	95%
Uncond.	2.8	3.2	0.9	2.4	2.8	0.9	-1.4	1.7
Single-Predic.								
Default Spread	2.9(.43)	3.2	0.9(.49)	2.5(.37)	2.9	0.9(.47)	-1.4	1.6
Dividend Yield	3.8(.02)	3.2	1.2(.05)	3.4(.00)	2.8	1.2(.01)	-1.4	1.8
Volatility (VIX)	3.8(.01)	3.2	1.2(.03)	3.4(.00)	2.8	1.2(.04)	-1.2	1.7
Aggregate Flow	3.0(.25)	3.3	0.9(.43)	2.6(.23)	2.9	0.9(.49)	-1.3	1.8
Multiple-Predic.								
All predictors	3.6(.08)	3.1	1.1(.11)	2.9(.17)	2.9	1.0(.23)	-1.1	1.7
Combination	3.2(.08)	3.0	1.0(.09)	2.8(.07)	2.6	1.1(.09)	-1.2	1.7

Table X

Performance across Investment Categories (Continued)

Panel C Managed Futures

	Return (Ann.)			Fung-Hsieh Alpha (Ann.)			Quantiles	
Nb. funds: 20	$\widehat{\mu}$	$\widehat{\sigma}_{tot}$	SR	$\widehat{\alpha}$	$\widehat{\sigma}_{res}$	IR	5%	95%
Uncond.	5.2	5.6	0.9	3.9	5.0	0.8	-2.0	3.0
Single-Predic.								
Default Spread	5.2(.55)	4.9	1.1(.28)	4.5(.33)	4.7	1.0(.23)	-2.0	2.8
Dividend Yield	6.1(.25)	5.9	1.0(.30)	5.3(.09)	5.4	1.0(.17)	-2.5	3.2
Volatility (VIX)	5.8(.32)	6.2	0.9(.52)	4.5(.30)	5.7	0.8(.54)	-2.3	3.7
Aggregate Flow	4.1(.90)	5.5	0.7(.89)	3.1(.82)	5.1	0.6(.81)	-2.4	2.9
Multiple-Predic.								
All predictors	3.5(.88)	6.9	0.5(.94)	2.2(.90)	6.2	0.3(.93)	-3.3	4.0
Combination	4.9(.77)	5.1	1.0(.47)	3.7(.66)	4.7	0.8(.52)	-1.9	2.9

Panel D Macro

	Return (Ann.)			Fung-Hsieh Alpha (Ann.)			Quantiles	
Nb. funds: 20	$\widehat{\mu}$	$\widehat{\sigma}_{tot}$	SR	$\widehat{\alpha}$	$\widehat{\sigma}_{res}$	IR	5%	95%
Uncond.	3.2	5.9	0.5	1.7	5.2	0.3	-2.7	2.7
Single-Predic.								
Default Spread	4.8(.06)	5.8	0.8(.06)	3.6(.02)	5.1	0.7(.02)	-2.0	3.0
Dividend Yield	2.9(.57)	6.3	0.5(.65)	1.4(.57)	5.2	0.3(.54)	-3.1	3.4
Volatility (VIX)	5.5(.01)	6.4	0.9(.02)	4.1(.00)	6.0	0.7(.00)	-2.6	3.1
Aggregate Flow	4.3(.20)	6.0	0.7(.21)	3.3(.09)	5.6	0.6(.14)	-2.7	3.3
Multiple-Predic.								
All predictors	3.4(.40)	5.8	0.6(.62)	2.1(.33)	5.4	0.4(.38)	-2.6	3.3
Combination	4.8(.00)	6.0	0.8(.01)	3.1(.01)	5.2	0.6(.01)	-2.3	3.2

Panel D Emerging Markets

	Return (Ann.)			Fung-Hsieh Alpha (Ann.)			Quantiles	
Nb. funds: 20	$\widehat{\mu}$	$\widehat{\sigma}_{tot}$	SR	$\widehat{\alpha}$	$\widehat{\sigma}_{res}$	IR	5%	95%
Uncond.	7.7	12.0	0.6	6.1	9.8	0.6	-6.0	5.7
Single-Predic.								
Default Spread	7.6(.51)	13.7	0.6(.74)	6.2(.45)	10.7	0.6(.58)	-6.8	6.0
Dividend Yield	5.3(.90)	11.3	0.5(.85)	3.9(.88)	8.9	0.4(.81)	-7.2	4.3
Volatility (VIX)	7.8(.39)	11.9	0.7(.35)	6.1(.47)	10.0	0.6(.49)	-5.8	5.5
Aggregate Flow	6.0(.91)	12.4	0.5(.93)	4.9(.87)	10.4	0.5(.87)	-6.9	5.9
Multiple-Predic.								
All predictors	4.4(.96)	13.9	0.3(.98)	3.9(.89)	11.2	0.3(.93)	-7.1	5.8
Combination	8.2(.21)	12.5	0.7(.34)	6.5(.28)	10.0	0.7(.32)	-7.2	5.9

Table X

Performance across Investment Categories (Continued)

Panel F Convertible Arbitrage

	Return (Ann.)			Fung-Hsieh Alpha (Ann.)			Quantiles	
Nb. funds: 20	$\widehat{\mu}$	$\widehat{\sigma}_{tot}$	SR	$\widehat{\alpha}$	$\widehat{\sigma}_{res}$	IR	5%	95%
Uncond.	3.2	6.3	0.5	2.4	4.7	0.5	-2.4	2.8
Single-Predic.								
Default Spread	3.4(.26)	6.3	0.5(.28)	2.6(.32)	4.7	0.6(.38)	-2.0	3.1
Dividend Yield	4.2(.00)	6.8	0.6(.04)	3.2(.02)	5.0	0.6(.07)	-2.3	3.1
Volatility (VIX)	4.4(.02)	8.3	0.5(.30)	3.0(.10)	6.1	0.5(.41)	-2.9	3.5
Aggregate Flow	1.9(.97)	6.0	0.3(.96)	1.6(.93)	4.6	0.3(.90)	-2.7	2.2
Multiple-Predic.								
All predictors	2.7(.59)	6.5	0.4(.67)	2.1(.58)	4.5	0.5(.58)	-2.4	2.2
Combination	3.9(.00)	6.5	0.6(.02)	3.0(.01)	4.5	0.7(.01)	-2.0	2.9

Panel G Event-Driven

	Return (Ann.)			Fung-Hsieh Alpha (Ann.)			Quantiles	
Nb. funds: 20	$\widehat{\mu}$	$\widehat{\sigma}_{tot}$	SR	$\widehat{\alpha}$	$\widehat{\sigma}_{res}$	IR	5%	95%
Uncond.	4.8	5.3	0.9	4.4	3.5	1.2	-2.4	2.2
Single-Predic.								
Default Spread	5.7(.09)	5.7	1.0(.27)	5.1(.17)	3.6	1.4(.24)	-2.7	2.5
Dividend Yield	6.2(.02)	5.3	1.2(.04)	5.8(.02)	3.5	1.6(.02)	-2.2	2.7
Volatility (VIX)	6.4(.01)	4.9	1.3(.01)	5.9(.00)	3.6	1.6(.02)	-2.1	2.7
Aggregate Flow	4.4(.78)	5.9	0.7(.96)	3.9(.88)	3.9	1.0(.95)	-2.3	2.6
Multiple-Predic.								
All predictors	6.2(.04)	5.5	1.1(.08)	5.7(.04)	4.0	1.4(.17)	-2.2	2.6
Combination	5.8(.05)	5.3	1.1(.09)	5.4(.03)	3.9	1.4(.14)	-2.3	2.5

Panel H Fixed Income

	Return (Ann.)			Fung-Hsieh Alpha (Ann.)			Quantiles	
Nb. funds: 20	$\widehat{\mu}$	$\widehat{\sigma}_{tot}$	SR	$\widehat{\alpha}$	$\widehat{\sigma}_{res}$	IR	5%	95%
Uncond.	2.8	4.6	0.6	2.8	3.6	0.8	-2.7	1.7
Single-Predic.								
Default Spread	2.6(.46)	4.0	0.7(.23)	2.1(.73)	3.1	0.7(.44)	-1.7	1.3
Dividend Yield	4.9(.02)	3.9	1.3(.01)	4.6(.01)	3.3	1.4(.03)	-2.1	1.8
Volatility (VIX)	4.5(.00)	4.0	1.1(.03)	4.2(.00)	3.2	1.3(.00)	-1.6	1.8
Aggregate Flow	2.8(.41)	4.8	0.6(.50)	2.7(.47)	3.6	0.8(.40)	-2.5	1.9
Multiple-Predic.								
All predictors	2.4(.62)	5.3	0.4(.72)	1.9(.78)	3.8	0.5(.75)	-2.7	1.8
Combination	3.2(.24)	3.7	0.8(.08)	2.8(.38)	3.1	0.9(.17)	-1.6	1.4

Table X

Performance across Investment Categories (Continued)

Panel I Funds of Funds

	Return (Ann.)			Fung-Hsieh Alpha (Ann.)			Quantiles	
Nb. funds: 47	$\widehat{\mu}$	$\widehat{\sigma}_{tot}$	SR	$\widehat{\alpha}$	$\widehat{\sigma}_{res}$	IR	5%	95%
Uncond.	3.7	4.9	0.8	3.2	3.7	0.9	-2.4	2.1
Single-Predic.								
Default Spread	5.5(.02)	5.7	0.9(.01)	5.0(.01)	4.4	1.1(.02)	-2.5	2.9
Dividend Yield	5.5(.00)	5.4	1.0(.00)	4.8(.00)	4.2	1.1(.02)	-1.9	2.8
Volatility (VIX)	4.8(.01)	4.8	1.0(.01)	4.2(.01)	3.8	1.1(.03)	-2.0	2.3
Aggregate Flow	4.1(.21)	5.3	0.8(.43)	3.7(.14)	4.2	0.9(.48)	-2.3	2.7
Multiple-Predic.								
All predictors	3.7(.38)	5.8	0.6(.67)	3.1(.42)	4.3	0.7(.65)	-2.7	2.6
Combination	5.1(.00)	4.7	1.1(.00)	4.5(.00)	3.7	1.2(.00)	-1.9	2.3

Panel J Multi-Strategies

	Return (Ann.)			Fung-Hsieh Alpha (Ann.)			Quantiles	
Nb. funds: 25	$\widehat{\mu}$	$\widehat{\sigma}_{tot}$	SR	$\widehat{\alpha}$	$\widehat{\sigma}_{res}$	IR	5%	95%
Uncond.	7.5	4.3	1.8	6.9	3.5	2.0	-1.6	2.3
Single-Predic.								
Default Spread	7.4(.63)	4.6	1.6(.79)	6.9(.58)	4.0	1.7(.85)	-1.5	2.5
Dividend Yield	7.1(.77)	4.6	1.5(.78)	6.5(.76)	3.9	1.7(.88)	-1.3	2.6
Volatility (VIX)	9.1(.09)	4.8	1.9(.34)	8.4(.05)	4.4	1.9(.52)	-1.1	2.7
Aggregate Flow	6.1(.98)	4.6	1.3(.99)	5.7(.97)	3.8	1.5(.97)	-1.5	2.2
Multiple-Predic.								
All predictors	6.8(.61)	5.5	1.2(.75)	6.0(.77)	5.0	1.2(.97)	-2.3	3.4
Combination	7.4(.58)	4.0	1.8(.35)	6.8(.60)	3.6	1.9(.63)	-1.1	2.2

Table XI

Performance during the 2008 Crisis

In Panel A, we measure the impact of the 2008 crisis on the out-of-sample performance of the unconditional, single-predictor, and combination strategies based on annual rebalancing. The leftmost columns show the annualized excess mean ($\widehat{\mu}$) and the Sharpe ratio (SR) up to 2007, as well as the changes due to the 2008 crisis. We also report the 2008 cumulative returns over the entire year (Total), and over two subperiods (January-August, and September-December). The final columns report the average estimated unconditional mean and slope coefficient of the funds included in each portfolio in 2008. For comparison purposes, we also report the 2008 performance of hedge fund value-weighted (VW) and equally-weighted (EW) indices, as well as the SP500. Panel B repeats the analysis by allowing the unconditional, single-predictor, and combination strategies to be rebalanced monthly.

Panel A Predictive Signal–Annual Rebalancing (baseline case)

	Perf.(2007)		Change(2008)		Cumulative returns(2008)			Cross-fund avg.(2008)	
	$\widehat{\mu}$	SR	$\widehat{\mu}$	SR	Jan.-Aug.	Sep.-Dec.	Total	mean	slope
Uncond.	7.6	2.3	-1.7	-0.9	-1.7	-10.9	-12.4	.98	na
Single-Predic.									
Default Spread	9.4	2.0	-2.5	-0.8	-7.4	-13.3	-19.7	.68	-.52
Dividend Yield	8.4	1.8	-1.4	-0.4	-0.4	-7.4	-7.8	.67	-.32
Volatility (VIX)	8.2	2.0	-0.5	-0.2	4.0	-1.6	2.3	.89	.16
Aggregate Flow	8.6	2.3	-1.8	-0.7	-2.9	-9.5	-12.1	.89	.10
Multiple-Predic.									
Combination	8.6	2.5	-1.5	-0.7	-1.0	-8.5	-9.4	.84	-.30
VW Index	5.6	1.1	-1.9	-0.5	-6.9	-9.9	-15.8	na	na
EW Index	6.1	1.1	-1.7	-0.3	-4.5	-8.6	-12.8	na	na
SP500	5.4	0.4	-4.2	-0.3	-12.4	-29.0	-37.8	na	na

Panel B Predictive Signal–Monthly Rebalancing

	Perf.(2007)		Change(2008)		Cumulative returns(2008)			Cross-fund avg.(2008)	
	$\widehat{\mu}$	SR	$\widehat{\mu}$	SR	Jan.-Aug.	Sep.-Dec.	Total	mean	slope
Uncond.	8.7	2.6	-0.9	-0.4	-1.0	-0.9	–2.0	1.26	na
Single-Predic.									
Default Spread	9.5	2.2	-0.8	-0.3	-4.1	3.8	-0.5	1.19	.13
Dividend Yield	9.9	2.0	-0.6	-0.2	-3.1	6.3	3.1	1.17	.27
Volatility (VIX)	9.4	2.4	-0.2	-0.2	2.0	4.9	7.0	1.18	.27
Aggregate Flow	8.7	2.5	-0.1	-0.2	0.9	6.6	7.6	1.21	.23
Multiple-Predic.									
Combination	9.8	2.8	-0.5	-0.3	-1.4	4.9	3.4	1.21	.08

Table XII

2008 Cumulative Returns across Investment Categories

For each investment category, we compute the total cumulative 2008 returns (as well as the September-December cumulative returns in parentheses) for the unconditional, single-predictor, and combination strategies. For each portfolio, the last rebalancing date in December 31, 2007.

	Uncond.	Default	Dividend	Volatility	Agg. Flow	Combination
Long-Short	-17.7(-11.1)	-21.8(-12.2)	-17.5(-10.4)	-6.0(-4.9)	-13.6(-8.0)	-17.1(-10.7)
Mkt. Neutral	-6.4(-5.6)	-4.6(-6.7)	-0.7(2.2)	-1.3(-3.0)	-5.3(-6.0)	-2.8(-4.5)
Man. Future	1.8(1.6)	0.0(2.2)	2.2(3.6)	8.3(9.9)	6.2(5.0)	0.4(1.6)
Macro	-0.6(1.8)	1.5(0.8)	-3.7(-0.5)	15.4(12.2)	1.7(3.3)	0.0(1.5)
Emerging	-23.2(-18.6)	-35.9(-21.5)	-21.7(-14.7)	-16.4(-9.1)	-30.0(-21.3)	-28.1(-18.1)
Convertible	-24.8(-16.9)	-20.7(-15.6)	-21.6(-14.1)	-21.6(-14.7)	-26.8(-20.0)	-21.7(-14.9)
Event-Driven	-14.2(-13.3)	-17.4(-14.5)	-6.7(-6.6)	-3.8(-6.2)	-19.4(-17.5)	-6.6(-6.8)
Fixed Income	-17.9(-17.6)	-14.8(-14.8)	0.1(-4.1)	-5.9(-8.6)	-21.7(-20.1)	-8.1(-9.5)
F. of Funds	-21.4(-15.9)	-20.7(-13.9)	-18.2(-11.6)	-14.2(-10.2)	-21.0(-16.7)	-16.7(-11.3)
Multi-Strategy	-8.1(-8.1)	-10.9(-9.7)	-6.0(-6.3)	15.4(5.8)	-12.3(-11.8)	-1.1(-4.5)

Table XIII
Illiquidity Measurement

We measure hedge fund illiquidity by estimating an AR(3) using each fund innovations from the predictive regression. For each investment category, we report the cross-sectional median and 25-75% quantiles (in parentheses) of the estimated coefficient, $\widehat{\rho}_k$, associated with lag k ($j = 1, ..., 3$). We also compute the proportion of funds in the population which exhibit no serial correlation for each lag k (associated standard deviation shown in parentheses). The results are based on monthly data between January 1994 and December 2007.

	First lag ρ_1		Second lag ρ_2		Third lag ρ_1	
	Coefficient	Proportion	Coefficient	Proportion	Coefficient	Proportion
Long-Short	.00 (-.13,.10)	26.8 (1.9)	-.06 (-.18,.05)	29.6 (2.0)	-.03 (-.11,.06)	5.2 (1.4)
Mkt. Neutral	.01 (-.12,.14)	29.3 (3.8)	-.09 (-.23,.01)	31.6 (3.8)	-.02 (-.12,.06)	8.2 (3.8)
Man. Future	-.06 (-.16,.04)	23.8 (3.4)	-.12 (-.21,-.02)	42.7 (3.1)	-.04 (-.13,.04)	8.9 (2.2)
Macro	-.03 (-.15,.06)	23.2 (3.7)	-.13 (-.22,-.01)	41.1 (3.7)	-.03 (-.13,.05)	12.7 (4.9)
Emerging	.05 (-.07,.16)	35.7 (3.8)	-.05 (-.17,.06)	24.7 (2.9)	-.01 (-.09,.06)	0.0 (2.6)
Convertible	.21 (.08,.33)	65.5 (5.2)	-.10 (-.23,.03)	35.5 (4.2)	.00 (-.09,.06)	0.0 (3.8)
Event-Driven	.07 (-.04,.16)	30.3 (3.9)	-.01 (-.14,.09)	22.3 (3.1)	-.02 (-.10,.06)	1.0 (3.3)
Fixed Income	.08(-.06,.20)	35.5 (2.9)	-.09(-.23,.03)	28.7 (3.4)	-.02(-.11,.07)	3.4 (3.9)
F. of Funds	.04 (-.06,.15)	21.1 (1.4)	-.14 (-.28,-.02)	50.8 (1.5)	.00 (-.07,.08)	0.0 (1.0)
Multi-Strategy	.02 (-.10,.14)	26.9 (2.0)	-.12 (-.26,.00)	44.0 (2.1)	-.01 (-.09,.06)	0.0 (1.5)
All Funds	.02 (-.10,.13)	26.2 (0.9)	-.09 (-.22,.03)	37.0 (0.9)	-.02 (-.10,.06)	2.1 (0.5)

Figure 1

Detecting Predictability from the Data

The figure shows the distribution of the fund estimated slope coefficient, $\widehat{b}$, in the three cases where: 1) the fund is unpredictable (i.e., its true slope coefficient, b, equals zero); 2) is predictable and has a negative relation with the predictor (i.e., $b<0$); 3) 2) is predictable and has a positive relation with the predictor (i.e., $b>0$). To determine whether the fund is predictable from the data, we set up the significance level, γ^*, and the implied thresholds, $b^-_{\gamma^*}$ and $b^+_{\gamma^*}$, that form the boundaries of the two significance regions (on the left and right side of zero). If the estimated slope coefficient, $\widehat{b}$, falls into one of the two significance regions (i.e., $\widehat{b}$ is significant), the fund is considered as predictable.

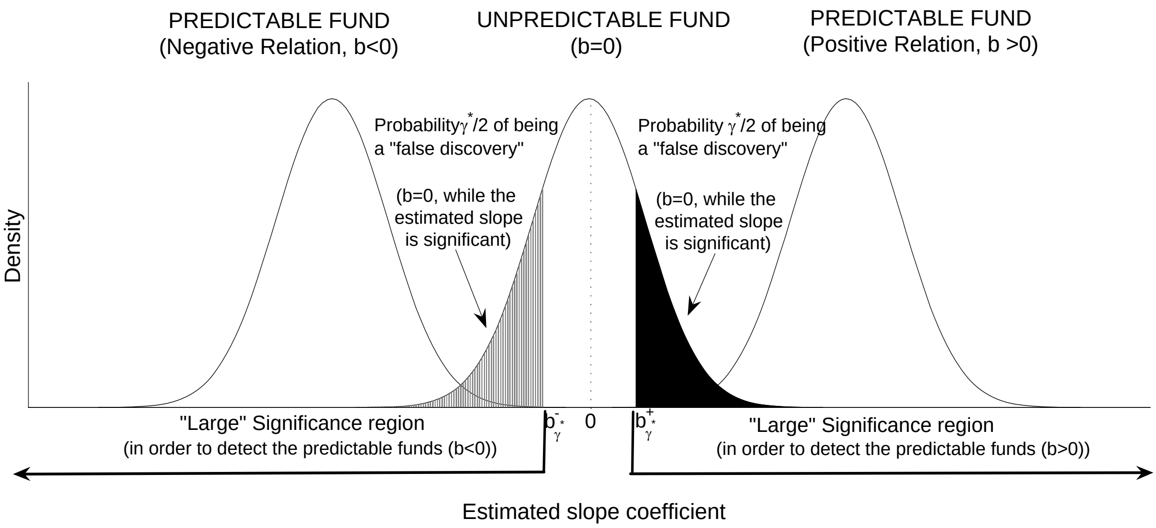


Figure 2

Predictive Signal and Predictor Value

We examine the relation between the fund predictive signal, $\widehat{t}(\mu_{i,t})$ (i.e., its conditional mean t-statistic), and the predictor value, $z_{j,t}$ generating the signal across three different predictors (J=3). $z_{j,t}$ is standardized so that a value of $z_t = 1$ indicates the predictor is one standard deviation above its average. We assume that the fund unconditional signal, $\widehat{t}(\mu_i)$, is equal to 5.0 (as in our empirical results to be presented). The low slope signal of predictor 1 combined with the high predictor value (signal 1) leads to a very low predictive signal. On the contrary, the slope signals of predictors 2 and 3 are higher and lead to an increase in the predictive signal from its unconditional value of 5.0.

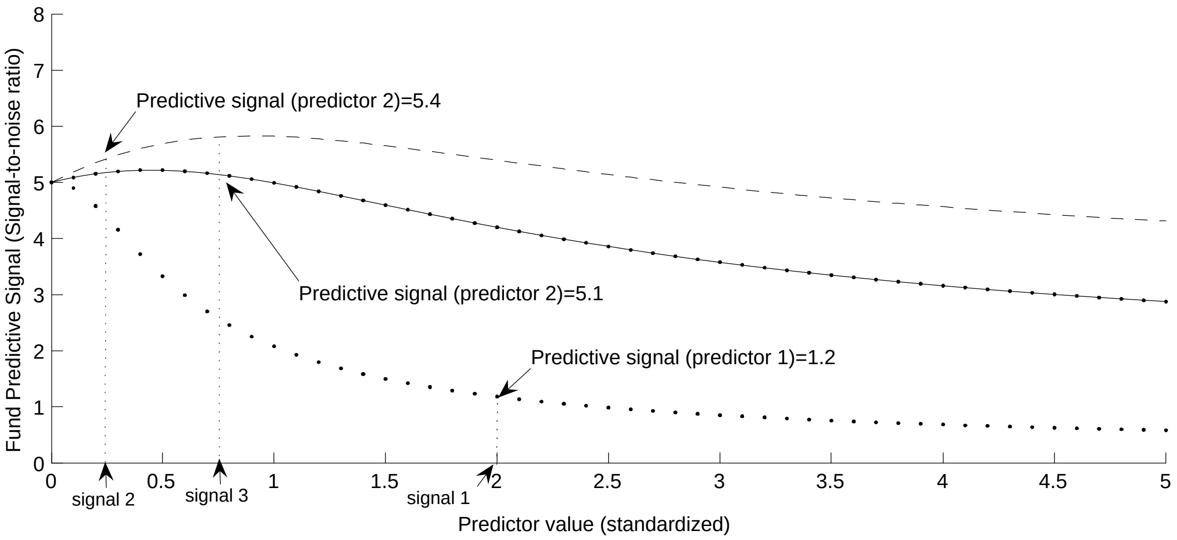
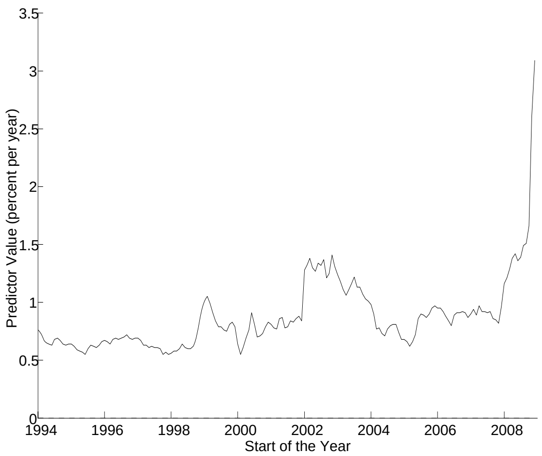
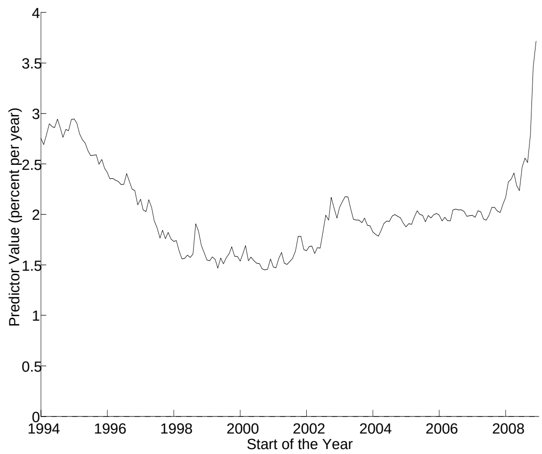


Figure 3
Evolution of the Predictors

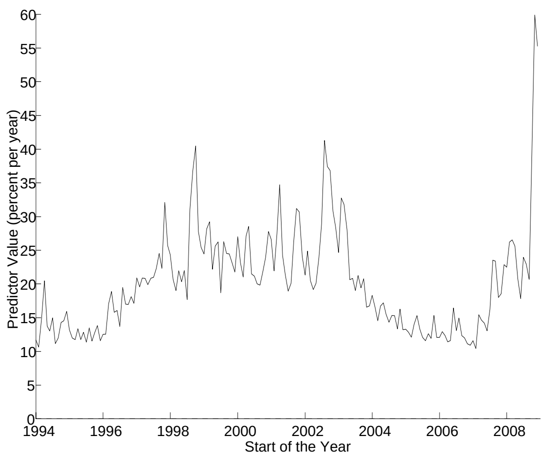
Each panel shows the time-variation of the different variables used to predict individual fund returns. Default spread is the yield differential between Moodys BAA-rated and AAA-rated bonds. Dividend yield is the total cash dividends on the value-weighted CRSP index over the previous 12 months divided by the current level of the index. Volatility is obtained from the VIX., and Aggregate flows is calculated as the value-weighted percentage in- and outflows into the hedge funds contained in our database. The graphs are based on monthly observations from January 1994 to December 2008.



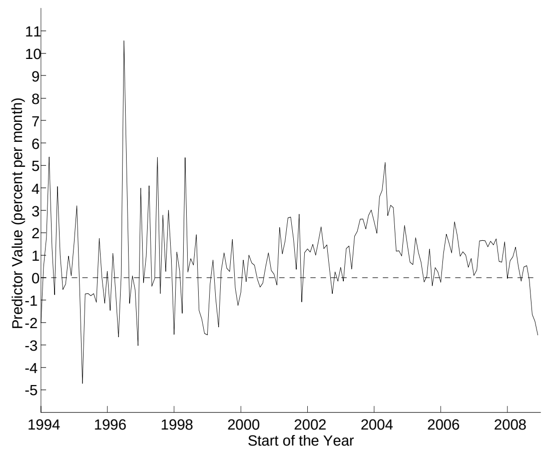
(A) Default Spread



(B) Dividend Yield



(C) Volatility (VIX)



(D) Aggregate Flow