Hedge Fund Return Predictability Under the Magnifying Glass*

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ABSTRACT

This paper develops a unified approach to comprehensively analyze individual hedge fund return predictability, both in- and out-of-sample. In-sample, we find that variation in hedge fund performance across changing market conditions is both widespread and economically significant. The predictability pattern across funds is consistent with economic rationale, and largely reflects differences in key hedge fund characteristics, such as leverage or capacity constraints. Out-of-sample, we show that a very simple strategy that combines the funds' return forecasts obtained from individual predictors delivers superior performance, even during the 2008 financial crisis. Importantly, we show that in- and out-of-sample predictability are closely related, contrary to the results documented in the previous literature.

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I Introduction

It is well established that the expected returns on financial assets, such as bonds and equities, depend on business conditions (e.g., Keim and Stambaugh (1986), Fama and French (1989)). Since mutual funds and hedge funds hold these assets, it is natural to wonder if their performance exhibit similar regularities. The empirical results documented by Ferson and Qian (2004) or Moskowitz (2000) show that mutual fund performance is higher in recessions than in expansions. For hedge funds, academic evidence on return predictability is relatively scarce. Hedge funds differ from mutual funds because they face fewer constraints, allowing managers to better exploit their skills or to leverage their positions. Because of this flexibility, their performance might be even more sensitive to economic conditions. For instance, the superior skills that their managers claim to have may best apply under specific market conditions. In addition, many hedge funds rely heavily on leverage, which might be curtailed in bad times.

In a recent study, Avramov, Kosowski, Naik, and Teo (2011; AKNT) look at the portfolio implications of hedge fund return predictability. Specifically, they apply Bayesian conditional strategies to the universe on individual hedge funds. Their paper shows that exploiting the predictive ability of macro variables greatly improves out-of-sample performance. However, it does not examine the cross-fund patterns in predictability. These patterns are likely to provide important insights on the dynamics of hedge fund returns, both within and across investment styles. In addition, they may be critical in explaining when and why the conditional strategies outperform out-of-sample.

The contribution of this paper is precisely to address these issues by applying a novel and unified approach to comprehensively analyze hedge fund return predictability, both in- and out-of-sample. In-sample, we determine to which extent individual fund returns vary over time, as well as the specific contribution of each predictive variable. Out-of-sample, we follow AKNT and examine whether conditional strategies can successfully exploit predictability. However, we depart from their paper in one key aspect: instead of using their sophisticated Bayesian approach, we rely on extremely simple trading rules. This simplicity permits a deep understanding of the drivers of out-of-sample performance and its links with in-sample predictability.

To assess the extent of in-sample return predictability in the entire fund population, we determine the proportion of funds having future returns that are (i) negatively related; (ii) unrelated; or (iii) positively related to each macro variable we consider. Importantly, this approach allows to distinguish between true and spurious predictability, because it explicitly accounts for funds that exhibit predictability by luck alone. To measure predictability out-of-sample, we examine the performance of *single-predictor* strategies that select, for each predictor and at each rebalancing date, the top decile of funds exhibiting the highest conditional mean. In addition to its simplicity, each strategy uses predictive information parsimoniously–that is, only when the predictor values depart from their long run level. However, when the predictor's forecast accuracy is poor, even a parsimonious use of predictive information may not be economically valuable. To address this issue, we advocate the use of a *combination* strategy that averages the fund return forecast obtained from each predictor separately. Intuitively, by diversifying across forecasts, the combination strategy should help reduce the impact of poor information quality, just like a portfolio reduces risk by diversifying across assets.

We apply our methodology to the monthly returns of around 8,000 hedge funds collected from five different providers (BarclayHedge, TASS, HFR, CISDM and MSCI). To track changes in business conditions, we use a set of four macro variables: the default spread, the dividend yield, the VIX index, and the net aggregate flows into the hedge fund industry. The econometric framework developed here extends past work to address the small sample bias in predictive regressions, accommodating both return and alpha predictability. In addition, we explicitly control for return autocorrelation arising from illiquid positions undertaken by hedge funds.

Starting with the in-sample analysis, we document ample evidence of return predictability between January 1994 and December 2007. Specifically, we find that 60.5% of the funds in the population have expected returns that vary across changing business conditions. This variation is economically significant–for instance, a one standard deviation decrease in market volatility (VIX) causes an additional return above 6% per year for 25% of the fund population. This predictability is not driven by the time-varying premia of the risk factors commonly used in the literature. This result is consistent with AKNT who show that the major source of profitability for their Bayesian strategies comes from time-varying managerial skills (alpha).

Examining the different macro variables separately, we find that the predictability pattern across funds is strongly "asymmetric" because changes in the predictor value tend to drive individual fund returns in the same direction. Importantly, this pattern is largely consistent with economic rationale. For instance, we find that a high dividend yield signals lower future returns, suggesting a more limited access to leverage during recessions. This result is observed across all investment categories, except managed futures funds. Since these funds depend less on prime brokers' funding, they encounter fewer leverage constraints over the business cycle. Similarly, we observe a negative relation between performance and past inflows across all styles, consistent with the presence of capacity constraints documented by Naik, Ramadorai, and Stromquist (2007) on hedge fund indices. By taking a fund-level perspective, we can determine the fraction of funds facing these constraints. We find that an increase in flows leads to lower future returns for 33.2% of the funds in the population, and for 44.7% of the funds that operate on the crowded convertible bond market. Finally, periods of higher market uncertainty generally signal lower future performance. This is, for instance, the case for event-driven funds (37.8% of them), reflecting the greater deal failure rate in turbulent periods.

Turning to the analysis of out-of-sample predictability, we implement different conditional strategies by incorporating real-world constraints encountered by institutional investors. For one, to account for liquidity constraints (i.e., lock-up periods), we permit only annual portfolio rebalancing. The evidence shows that an unconditional portfolio that simply uses past returns to select funds performs well, consistent with Jagannathan, Malakhov, and Novikov (2010). This portfolio generates a Fung-Hsieh (FH) alpha, $\widehat{\alpha}$, and Information Ratio, IR of 5.8%, and 2.4 per year, respectively. For comparison, *single-predictor* strategies that use only one of the four macro variables to forecast returns underperform the unconditional portfolio on a risk-adjusted basis. Remarkably, the *combination* strategy achieves the highest performance, producing a FH alpha of 7.0% per year and an additional 50%-cumulative return over the unconditional portfolio. It exhibits a low tail risk, a low exposure to the FH risk factors (like a "pure alpha" strategy), as well as reasonable levels of turnover. In addition, the autocorrelation coefficients suggest that performance is not due to investing in illiquid funds.

When and why are the *single-predictor* strategies more likely to fail? These strategies exploit predictive information whenever the predictor value considerably moves away, either up or down, from its long run mean. However, in these two cases, the forecast accuracy differs significantly because of the "asymmetric" nature of predictability documented in-sample. To illustrate, consider the dividend yield. In recession, when its value is above average, funds with predictable returns tend to underperform as they face additional leverage constraints. As a result, exploiting predictability during such times should be more difficult. Consistent with this intuition, we show that the performance of the strategy falls substantially when the dividend yield is high. Overall, the predictability patterns documented in-sample largely explain when and why the conditional strategies outperform out-of-sample.

In contrast, the *combination* strategy generates a steady performance because it is less affected by the "asymmetry" in the predictive ability of each predictor. First, averaging across forecasts leads to a very conservative portfolio–on average, 80% of the chosen funds are common to the unconditional portfolio. While the benefits of this shrinkage effect are discussed in Rapach, Strauss, and Zhou (2010) in the context of the US stock index, we argue that they are even more important in a multi-asset setting because investors are potentially hit twice–both by choosing funds with low return predictability, and by excluding funds with high unconditional performance. Second, diversifying across predictors helps detect the (truly) predictable funds from the data. Indeed, the active portfolio chosen by the combination strategy (i.e., the remaining 20%) generates a FH alpha up to 5.3% per year over the unconditional portfolio.

The 2008 financial crisis featured extreme fluctuations of the predictor values away from their long run means, and as such, raises specific issues about the dynamics of hedge fund returns. Incorporating 2008 reveals that the risk-adjusted performance of the combination strategy is still superior to that of the unconditional portfolio ($\widehat{\alpha}$=6.0% versus 4.1%, IR=1.9 versus 1.2). Evaluating the stability in the predictors' forecasting ability during the crisis, we find evidence of structural breaks for both the default spread and the dividend yield, but not for the VIX. This result may explain why the VIX strategy resisted remarkably well in 2008, posting the lowest final quarter loss among all strategies. Finally, we measure the cost of the additional liquidity constraints imposed by hedge funds on their investors during the crisis, and find them to be substantial.

The overall evidence documented here makes several contributions. In-sample, we find that hedge fund return predictability is widespread and largely consistent with economic intuition, reflecting the importance of key hedge fund characteristics, such as leverage or capacity constraints. Out-of-sample, we show that a simple *combination* strategy that diversifies across forecasts is able to deliver superior performance. Finally, our results highlight the important links existing between in- and out-of-sample predictability, and contrast with the difficulties faced by previous studies to reconcile these two notions (e.g., Bossaerts and Hillion (1999), Goyal and Welch (2008)). By taking a multi-fund perspective, we show that the predictive ability of each macro variable is a fundamental driver of the performance of the conditional strategies.

The remainder of this paper proceeds as follows. Section II discusses the methodology. Section III describes the hedge fund data. Section IV contains the empirical results of the paper, along with the robustness tests. Finally, Section V concludes.

II Understanding Hedge Fund Return Predictability

A Measuring In-Sample Return Predictability

We attempt to predict future returns on M individual hedge funds using J aggregate variables that potentially capture evolving economic conditions. Predictability is analyzed based on the time series predictive regression, run separately for each fund,

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

The dependent variable $r_{i,t+1}$ denotes the time $t+1$ excess hedge fund return (over the riskfree rate), $Z_{j,t}$ $(j = 1, ..., J)$ is the time t realized value of the j-th predictive variable, $b_{i,0}$ is the intercept, $b_{i,j}$ is the slope coefficients associated with each predictor, and $u_{i,t+1}$ denotes the unpredictable fund specific innovation.

Hedge funds follow a wide range of investment strategies, even within pre-established investment styles. Hence, studying individual funds rather than broad indices should allow for a more precise assessment of hedge fund return predictability. Specifically, to determine the predictive ability of variable j on the cross-section of fund returns, we decompose the population into three distinct categories:

- funds with unpredictable returns ($b_{i,j} = 0$);
- funds with predictable returns and a negative relation with predictor j ($b_{i,j} < 0$);
- funds with predictable returns and a positive relation with predictor j ($b_{i,j} > 0$).

Then, we measure the proportions of funds in the population, denoted by $\pi_R^0(j)$, $\pi_R^-(j)$, and $\pi_R^+(j)$, that fall into one of these three categories. The estimation procedure borrows from Barras, Scaillet, and Wermers (2010; BSW), and uses as input the estimated slope coefficients, $\widehat{b}_{i,j}$, across all funds. Importantly, this approach allows to measure true predictability, because it explicitly accounts for funds that exhibit predictability by luck alone (i.e., funds with statistically significant $\widehat{b}_{i,j}$, while their true coefficient, $b_{i,j}$, equals zero). We refer the interested reader to BSW for further detail.

While the predictive regression in Equation (1) helps determine whether a given fund exhibits predictable returns, there are various sources of predictability. First, benchmark expected returns (risk premia) can vary with changing economic conditions. Second, hedge fund managers may have skills in security selection and benchmark timing that depend on the state of the economy. In this case, the private information held by managers correlate with the predictive variables, making fund alphas predictable. To capture this intuition, we follow past work (e.g., Christopherson, Ferson, and Glassman (1998)), and model the dynamics of hedge fund return using

$$r_{i,t+1} = a_{i,0} + \sum_{j=1}^{J} a_{i,j} \cdot Z_{j,t} + \beta_i' f_{t+1} + \epsilon_{i,t+1}, \quad (2)$$

where f_{t+1} is the K-vector of portfolio-based benchmark excess returns in time $t+1$, β_i is the K-vector of fund risk loadings, $a_{i,0}$ is the intercept, $a_{i,j}$ is the alpha slope coefficient associated with each predictor, and $\epsilon_{i,t+1}$ is the idiosyncratic fund-specific term. We decompose again the fund population into three predictability categories, now based on alpha variations, and denote by $\pi_\alpha^0(j)$, $\pi_\alpha^-(j)$, and $\pi_\alpha^+(j)$, the proportions of funds whose alphas are unrelated ($a_{i,j} = 0$), negatively related ($a_{i,j} < 0$), and positively related ($a_{i,j} > 0$) to predictor j, respectively.

For a given fund i, we can easily determine the source of predictability by comparing the slope coefficients in Equations (1) and (2). For one, if the explanatory power of predictor j is entirely driven by risk factors (as opposed to alpha), we would observe $b_{i,j} \neq 0$ and $a_{i,j} = 0$. This idea can be extended to examine the source of predictability in the entire cross-section of hedge funds by comparing the proportions of funds with predictable returns, $\pi_R^-(j)$ and $\pi_R^+(j)$, with the proportions of funds with predictable alphas, $\pi_\alpha^-(j)$ and $\pi_\alpha^+(j)$.

Given the large number of factors used in Equation (2) (typically seven factors in the Fung-Hsieh (2004) model), we assume that benchmark risk loadings are time-invariant. Using more parsimonious models, Bollen and Whaley (2009) and Patton and Ramadorai (2010) find that hedge fund betas are subject to structural breaks. Such breaks are less of a concern here since we are mostly interested in the estimated slope coefficients, $\widehat{a}_{i,j}$. While unmodeled beta variations can potentially bias the estimated unconditional alpha, they do not affect $\widehat{a}_{i,j}$ as long as the relation between the predictors and factors remains unchanged after the break.[1] To empirically verify this property, we examine the impact of changing betas associated with the prominent market and size factors. Following Fung et al. (2008), we allow for breaks after September 1998 and March 2000 and find in unreported results that the estimated proportion of predictable funds in the population remain virtually unchanged.

B Measuring Out-of-Sample Return Predictability

B.1 The Single-Predictor Strategy

Previous studies on mutual funds and hedge funds (e.g., Elton, Gruber, and Blake (1996), Carhart (1997)) typically rank and select funds based on unconditional perfor-

[1] To see this, consider a simple model with one centered predictor, $z_{j,t} = Z_{j,t} - E(Z_{j,t})$, one factor, $f_{k,t+1}$, and one structural break at time $t+1 = \tau^*$: $r_{i,t+1} = \alpha_{i,0} + a_{i,j} \cdot z_{j,t} + \beta_{i,k} f_{k,t+1} + \beta_{i,k}^* f_{k,t+1}^* + \epsilon_{i,t+1}$, where $\alpha_{i,0}$ is the unconditional alpha and $f_{k,t+1}^* = f_{k,t+1} \cdot 1_{\{t+1 \geq \tau^*\}}$. Assuming that the relation between $z_{j,t}$ and $f_{k,t+1}$ is constant over time, we have $cov(z_{j,t}, f_{k,t+1}^* | f_{k,t+1}) = 0$, and the bias in $\widehat{a}_{i,j}$ in a constant-beta model is equal to zero: $E(\widehat{a}_{i,j} - a_{i,j}) = \beta_{i,k}^* \frac{cov(z_{j,t}, f_{k,t+1}^* | f_{k,t+1})}{var(z_{j,t} | f_{k,t+1})} = 0$. However, the estimated unconditional alpha is biased: $E(\widehat{\alpha}_{i,0} - \alpha_{i,0}) = \beta_{i,k}^* E(f_{k,t+1}^*) \neq 0$.

mance measures. Our selection process simply extends this approach to an conditional setting. Initially, we consider a *single-predictor* strategy ($J = 1$) to measure the out-of-sample predictive ability of each macro variable separately, and turn to richer dynamics below.

We implement this strategy for each predictor j ($j = 1, ..., J$) using three steps. The first step estimates, at each rebalancing time t (e.g., each year) and for each existing fund ($i = 1, ..., M_t$), the conditional (excess) mean,

$$\widehat{\mu}_{i,t}\left(j\right) = \widehat{\mu}_i + \widehat{b}_{i,j} z_{j,t}, \tag{3}$$

where $\widehat{\mu}_i$ is the estimated unconditional mean, $\widehat{b}_{i,j}$ is the estimated slope coefficient, and $z_{j,t}$ is the centered predictor value, $z_{j,t} = Z_{j,t} - \overline{Z}_j$, with $\overline{Z}_j$ being the sample mean computed using data up to date t. The conditional mean is not estimated with the same accuracy across funds with varying lives and investment strategies. To account for these differences, the second step consists of computing the t-statistic of the estimated conditional mean:

$$t(\widehat{\mu}_{i,t}(j)) = \frac{\widehat{\mu}_{i,t}\left(j\right)}{\widehat{var}(\widehat{\mu}_{i,t}\left(j\right))^{\frac{1}{2}}}, \tag{4}$$

where $\widehat{var}(\widehat{\mu}_{i,t}\left(j\right))$ is the estimated variance of $\widehat{\mu}_{i,t}\left(j\right)$. Since the conditional t-statistic indicates how precisely the conditional mean is estimated, it should improve the fund selection process.[2] The third step of our dynamic setup consists of investing in the top decile of funds with the highest $t(\widehat{\mu}_{i,t}\left(j\right))$. This portfolio is held over the next period, after which the selection procedure is repeated (based on the new predictor value at time $t+1$).

The investment process followed by the single-predictor strategy is straightforward. Specifically, let the unconditional t-statistic be $t\left(\widehat{\mu}_i\right) = \widehat{\mu}_i / \widehat{var}(\widehat{\mu}_i)^{\frac{1}{2}}$, and let the slope t-statistic be $t(\widehat{b}_{i,j}) = \widehat{b}_{i,j} / \widehat{var}(\widehat{b}_{i,j})^{\frac{1}{2}}$. Using Equation (4), we can write the conditional t-statistic of fund i as a weighted average of the unconditional and slope t-statistics:

$$\begin{aligned} t(\widehat{\mu}_{i,t}\left(j\right)) &= \left(\frac{\widehat{var}(\widehat{\mu}_i)}{\widehat{var}(\widehat{\mu}_{i,t}\left(j\right))}\right)^{\frac{1}{2}} t\left(\widehat{\mu}_i\right) + \left(\frac{\widehat{var}(\widehat{b}_{i,j})}{\widehat{var}(\widehat{\mu}_{i,t}\left(j\right))}\right)^{\frac{1}{2}} z_{j,t} \cdot t(\widehat{b}_{i,j}) \\ &= w_{\mu}\left(z_{j,t}\right) \cdot t\left(\widehat{\mu}_i\right) + w_{b,j}\left(z_{j,t}\right) \cdot t(\widehat{b}_{i,j}), \end{aligned} \tag{5}$$

where the weights, w_{μ} and $w_{b,j}$, depend on the difference, $z_{j,t}$, between the current value

[2] In an unconditional setting, the use of the t-statistic as an improved performance measure is advocated, among others, by Kosowski et al. (2006) and Kosowski, Naik, and Teo (2007).

of the predictive variable, $Z_{j,t}$, and its long run mean $\overline{Z}_j$.

Essentially, when $Z_{j,t}$ is close to $\overline{Z}_j$, the strategy invests in the "unconditional" portfolio–the portfolio holding the top decile of funds with the highest unconditional t-statistic, $t\left(\widehat{\mu}_i\right)$. However, when $Z_{j,t}$ departs from $\overline{Z}_j$, the predictable component, $z_{j,t}b_{i,j}$, grows large, and the strategy invests in the "slope" portfolio–the portfolio holding the top decile of funds with the highest slope t-statistic, $t(\widehat{b}_{i,j}) \cdot sign(z_{j,t})$, where $sign(z_{j,t})$ denotes the sign of $z_{j,t}$. That is, the slope t-statistic is multiplied by the sign of $z_{j,t}$ to guarantee that the slope portfolio contains funds with the correct exposure ($\widehat{b}_{i,j} < 0$ when $z_{j,t} < 0$, and vice-versa).

In a large fund population, it is unlikely that funds with the highest unconditional mean are also those exhibiting the strongest return predictability. Therefore, one important challenge for investors is to address the trade-off between unconditional and predictable performance. Figure 1 illustrates this issue using our comprehensive hedge fund dataset (discussed below). Plot A shows the relation between the average t-statistic of funds included in the unconditional portfolio and the default spread (using other predictors provide similar insights).[3] To ease interpretation, $z_{j,t}$ is standardized, i.e., a value of one indicates that the predictor value is one standard deviation above its average. In a nutshell, we find that funds with high unconditional mean tend to have unpredictable returns. While initially large, the conditional t-statistic quickly goes down as $|z_{j,t}|$ increases because of the low and noisy estimate of the predictable component, $z_{j,t}\widehat{b}_{i,j}$. Plot B shows the results for the slope portfolio. In this case, we observe the exact opposite pattern, i.e., the conditional t-statistic of the slope portfolio is initially low, implying that funds with predictable returns tend to have low unconditional mean.

Besides its simplicity, the single-predictor strategy naturally incorporates this trade-off into the fund selection process. Specifically, Equation (5) reveals that this strategy invests in the slope portfolio only when the predictor, $Z_{j,t}$, is sufficiently far away from its long-run mean (i.e., when the fund estimated predictive component, $z_{j,t}\widehat{b}_{i,j}$, is large enough). This investment process is illustrated in Plot C.

Please insert Figure 1 here

[3] Specifically, for each fund i included in the unconditional portfolio in month t, we use past returns (over the last 36 months) to estimate $t\left(\widehat{\mu}_i\right)$, $\widehat{var}(\widehat{\mu}_i)$, $t(\widehat{b}_{i,j})$, and $\widehat{var}(\widehat{b}_{i,j})$. Then, we compute averages of these quantities across funds ($i \in$ unconditional portfolio in month t) and months ($t = 1, ..., T$). These averages are inserted in Equation (5) to compute $t(\widehat{\mu}_t^U)$, as a function of the predictor value, $z_{j,t}$.

B.2 The Combination Strategy

The trade-off between unconditional and predictable performance suggests that investing in the slope portfolio is only advisable when $|z_{j,t}|$ is sufficiently large. But even in this situation, the performance of the single-predictor strategies can deteriorate if the return forecasts are not accurate.

First, due to estimation errors, it may be quite difficult to detect the (truly) predictable funds from the data (those funds with $z_{j,t}b_{i,j} > 0$). To illustrate, Plot C in Figure 1 clearly shows that, empirically, the slope signal is less precise than the unconditional signal–the maximum value for the t-statistic of the unconditional portfolio equals 3.5, as opposed to only 1.6 for the slope portfolio. This suggests that when $|z_{j,t}|$ gets large, the single-predictor strategy may simply replace funds with high unconditional performance for funds exhibiting low levels of return predictability.

Second, even if at some point in time, we can precisely estimate the slope coefficients associated with a given predictor j, numerous factors, such as the investors' search for successful forecasting models, technological shocks, or institutional changes, can make the predictive model misspecified (e.g., Timmermann (2008)). Since we expect both the identity of the relevant predictors as well as their associated slope coefficients to change over time, the single-predictor model considered so far may sometimes convey wrong signals about future performance, leading to a poor fund selection.

To address estimation risk and model misspecification, we implement an alternative conditional strategy building on the combination forecast literature (e.g., Bates and Granger (1969), Timmermann (2006)). Specifically, for each existing fund i at the rebalancing time t ($i = 1, ..., M_t$), we estimate its conditional t-statistic, $t(\widehat{\mu}_{i,t}(j))$, using each predictor j separately ($j = 1, ..., J$). Second, we compute the simple average across all J conditional t-statistics:

$$t(\widehat{\mu}_{i,t}) = \frac{1}{J}\sum_{j=1}^{J} t(\widehat{\mu}_{i,t}(j)) = w_{\mu} \cdot t(\widehat{\mu}_i) + \frac{1}{J}\sum_{j=1}^{J} w_{b,j}(z_{j,t}) \cdot t(\widehat{b}_{i,j}), \tag{6}$$

where $w_{\mu} = \frac{1}{J}\sum_{j=1}^{J} w_{\mu}(z_{j,t})$.[4] We ultimately design an investment strategy that holds the top decile of funds with the highest combination t-statistic, $t(\widehat{\mu}_{i,t})$.

This *combination* strategy exhibits several appealing properties. First, since it is unlikely to observe extreme values for all predictors simultaneously, the total weight,

[4]While more complex weighting schemes exist, the simple average tends to perform well, as the weights do not have to be estimated (see Timmermann (2006)). As an alternative to combination forecast, previous papers use Bayesian averaging, where the weight associated with each predictive model depends on the model prior distribution (e.g., Avramov (2002)).

w_μ, associated with the fund unconditional t-statistic, $t(\widehat{\mu}_i)$, remains high. At the same time, the importance of the slope signals in the investment process decreases because each individual weight, $w_{b,j}(z_{j,t})$, is divided by J. The combination strategy shrinks the portfolio towards the unconditional portfolio and reduces the negative impact of both estimation risk and model misspecification (see Rapach, Strauss, and Zhou (2010) for a discussion in a single-asset setting). In particular, Hendry and Clements (2004) show that combining forecasts provides a good hedge against structural breaks in the data generating process. Second, similar to portfolio diversification, combining forecasts generally reduces the out-of-sample forecast error variance, and should improve the detection of funds with (truly) predictable returns.

Alternatively, we could try to improve on the single-predictor model by including all predictors simultaneously in the predictive regression. However, as shown by Avramov (2002) and Goyal and Welch (2008), the out-of-sample forecast errors of this multi-predictor model are large, as multiple slope coefficients are estimated with less accuracy. Since there is no shrinkage towards the unconditional portfolio, performance deteriorates because large positions are taken in slope portfolios that exhibit low or no return predictability out-of-sample.[5] However, for comparative purposes, we also report the performance of the conditional strategy based on the multi-predictor model.

C Estimation Issues

C.1 Correcting for Small Sample Bias

It is well-known that the ordinary least-square (OLS) estimation of the predictive regression slope coefficients is subject to small-sample bias (e.g., Stambaugh (1999)). While this bias disappears in large enough samples, it is an important concern here because the return history for many hedge funds is short. For one, survivorship bias-free databases only start in January 1994.

In a nutshell, the small sample bias arises because the hedge fund innovation, $u_{i,t+1}$, in Equation (1) is contemporaneously correlated with the J-vector of predictor innovations, v_{t+1}.[6] That is, we can express the hedge fund innovation as $u_{i,t+1} = \phi_i' v_{t+1} + e_{i,t+1}$,

[5] To see why there is no shrinkage, note that in the multi-predictor case, the conditional t-statistic has a similar expression as in Equation (5): $t(\widehat{\mu}_i) = w_\mu(z_t) \cdot t(\widehat{\mu}_i) + w_b'(z_t) \cdot t(\widehat{b}_i)$, where z_t, w_b, and $t(\widehat{b}_i)$ are all J-vectors. When the k^{th} element of z_t gets large, the conditional strategy invests in the k^{th} slope portfolio that holds funds with the highest k^{th} slope t-statistic, $t(\widehat{b}_{i,k})$.

[6] Unless the J-vector of predictor innovations, v_{t+1}, is strongly correlated with news about current and future expected cash flows, there must be a contemporaneous correlation between v_{t+1} and $u_{i,t+1}$. Changes in future expected returns captured by v_{t+1} affect both prices and the contemporaneous fund return, $r_{i,t+1}$ (e.g., Cochrane (2008)).

where ϕ_i denotes the J-vector of innovation coefficients, and $e_{i,t+1}$ is the fund residual term (orthogonal to both υ_{t+1} and $Z_t = [Z_{1,t}, ..., Z_{J,t}]$).

As noted by Amihud and Hurvich (2004) and Amihud, Hurvich, and Wang (2008; AHW), if we include the J-vector υ_{t+1} as an additional explanatory variable and write

$$r_{i,t+1} = b_{i,0} + \sum_{j=1}^{J} b_{i,j} Z_{j,t} \ + \phi_i^{'} \upsilon_{t+1} + e_{i,t+1}, \tag{7}$$

the small-sample bias disappears because the orthogonality holds, i.e., $E\left(e_i \,|X, V\right) = 0$, where $e_i = [e_{i,2}, ..., e_{i,T+1}]'$, $X = [1, Z_1', ..., Z_T']$, and $V = [\upsilon_2', ..., \upsilon_{T+1}']$. Of course, we cannot observe the true innovation vector, thus we compute a proxy, υ_{t+1}^c, using the procedure proposed by AHW. After replacing υ_{t+1} with υ_{t+1}^c, we can compute the bias-corrected estimated slope coefficients, $\widehat{b}_{i,j}$, by applying standard OLS to the augmented regression in Equation (7). Using extensive simulation tests, AHW find that their approach achieves a substantial reduction in the small-sample bias ($\widehat{b}_{i,j}$ is not totally bias-free though, as we use υ_{t+1}^c instead of the true υ_{t+1}). While other approaches are also feasible, such as the bootstrap (Nelson and Kim (1993)), the AHW procedure is computationally much faster as it boils down to estimating a single regression for each fund. Given the great number of funds in our sample, computational efficiency is strongly appealing.

The framework proposed by AHW focuses on predictive return regressions. Here, we extend their methodology on several fronts: (i) to examine predictability in a richer setting that incorporates alpha predictability and different time horizons (monthly and quarterly); (ii) to account for potential hedge fund illiquidity, as discussed below. All the technical details on estimation are discussed in the appendix.

C.2 Accounting for Hedge Fund Illiquidity

Some hedge funds invest in illiquid assets, such as emerging market debt, asset-backed securities, or over-the-counter derivatives. Illiquidity tends to induce positively correlated residuals, $e_{i,t+1}$, in Equation (7) (see Getmansky, Lo, and Makarov (2004)). Failing to adjust for this correlation, we would overestimate the t-statistics of $\widehat{b}_{i,0}$, and $\widehat{b}_{i,j}$ for illiquid funds, and wrongly conclude that these funds have a high unconditional mean and/or highly predictable returns.

To explicitly control for illiquidity, we model the residual, $e_{i,t+1}$, of each fund i as an $AR(p)$ process $(i = 1, ..., M)$:

$$e_{i,t+1} = \sum_{l=1}^{p} \rho_{i,l} e_{i,t+1-l} + \xi_{i,t+1}, \tag{8}$$

where $\rho_{i,l}$ is the autoregressive coefficient at lag l $(l+1, ..., p)$, and $\xi_{i,t+1}$ is the innovation term. Using the estimated residuals, $\widehat{e}_{i,t+1}$, to obtain consistent autoregressive coefficient estimates, we compute the proportions of funds with non-zero coefficients ($\rho_{i,l} \neq 0$) at different lags. In unreported results, we find that 29.1% and 28.1% of the funds have a one-month and two-month lag coefficients different from zero, respectively, while the proportion falls to 4.9% at a three-month lag. Based on this evidence, we use an AR(2) model that we estimate for each fund separately to control for the cross-fund coefficient variation observed in the data.[7]

III Data Description

We use four economically motivated instruments to predict future hedge fund returns: the default spread, the dividend yield, the VIX, and aggregate fund flows. Given the relatively small number of monthly observations for hedge funds, model parsimony is an important consideration in our choice of predictors. Parsimony also avoids the search over a large number of predictors which could invoke data-mining concerns.[8] All predictors are observed at a monthly frequency and appropriately lagged to forecast future hedge fund excess returns.

The default spread is the yield differential between Moodys BAA- and AAA-rated bonds. Previous studies (e.g., Keim and Stambaugh (1986)) show that the default spread can predict future stock and bond returns. The dividend yield is the total of annual cash dividends on the value-weighted CRSP index divided by the current index level. Fama and French (1989) suggest that the dividend yield is a business cycle indicator that peaks in recession when expected returns required by investors are high. We also use the VIX index from the CBOE to proxy for changes in market uncertainty. Taylor, Yadav, and Zhang (2010) present evidence that implied volatilities help predict stock returns. Moreover, volatility may capture some of the option-like features in hedge fund returns (e.g., Agarwal and Naik (2004)). Aggregate flows are calculated as the

[7] As an alternative, we also compute the variance of the estimated regression coefficients using the Newey-West (1987) methodology, and find that the results (to be presented) remain unchanged.

[8] Patton and Ramadorai (2010) address the need for a parsimonious model by examining a large number of predictors and risk factors, and, for each fund, selecting one predictor and two factors based on a statistical criterion.

value-weighted percentage net inflows into our sample of hedge funds. As discussed in Naik, Ramadorai, and Stromqvist (2007) and Fung et al. (2008), new money can create capacity constraints, leading to lower future returns.

We evaluate hedge fund performance based on monthly net-of-fee returns of live and dead funds using a new database that aggregates, for the first time, data reported by five different providers (BarclayHedge, TASS, HFR, CISDM and MSCI). A key advantage of this approach is to reduce selection bias. Since there is little fund overlap across providers (Kosowski, Naik, and Teo (2007)), our universe of funds is likely to be closer to the true unobserved hedge fund population. To create this database, we are careful to remove duplicate funds that exist in several databases, as well as funds with multiple shareclasses.[9] In addition, we start our analysis in 1994 because prior to that date, databases did not keep track of dead funds. Finally to account for backfill bias, we exclude the first 12 months of data for each fund. To allow for a detailed interpretation of predictability results per strategy, we choose to group funds into 10 different investment styles. These are listed in Panel A of Table I which reports descriptive statistics for the hedge funds included in our sample. To estimate the predictive regression coefficients, we require each fund to have at least 36 monthly return observations, leading to a final sample of 7,991 funds between January 1994 and December 2007.[10]

We observe from Panel B that the default spread, the dividend yield, and the VIX exhibit high positive autocorrelation ($\rho = 0.95$, 0.97, and 0.84, respectively). These large coefficients highlight the importance of controlling for small sample bias in the estimation process. In addition, correlations across predictors are low on average, suggesting that each variable captures specific variations in economic conditions. In this context, the combination strategy could add value over individual predictors.

Finally, Panel C contains summary statistics for the benchmarks included in the Fung and Hsieh (2004) seven factor model.[11] Equity market is the S&P 500 return minus risk free rate, while equity size is the Wilshire small cap minus large cap return. Bond term and bond default proxy for the returns of 10–year Treasury bonds and 10–year Baa-rated bonds, respectively.[12] Finally, trend bond, trend currency, and trend

[9] We use two main approaches to identify duplicates between the databases. The first is based on a string comparison of fund names. The second compares fund returns based on their mean difference and correlations. When multiple shareclasses are identified we use the oldest US dollar shareclass.

[10] While this requirement may lead to survivorship bias, unreported results show that our results are robust to using funds with 24 monthly observations.

[11] We thank David Hsieh for making these factors available on his website.

[12] Note that the return "bond default" is very different from the predictor "default spread", just like the stock market return is very different from its dividend yield. The default spread is a highly persistent variable that helps forecast the return of defaultable bonds. However, a large part of this return is driven by unpredictable components (i.e., cash-flow and expected return news).

commodity capture the returns of straddle-type trend following strategies.

Please insert Table I here

IV Empirical Results

A In-Sample Return Predictability

We begin our empirical analysis by measuring in-sample return and alpha predictability across individual hedge funds over the period 1994-2007. Table II reports the evidence for all funds in the population, as well as for the different investment categories. The first row (Return) contains the estimated proportions of funds with predictable returns, $\pi_R^-(j)$ and $\pi_R^+(j)$, associated with each predictor using the (bias-corrected) estimated slope coefficients, $\widehat{b}_{i,j}$, in Equation (1). The last row-element displays the proportion of funds having predictable returns using all predictors simultaneously, $\widehat{\pi}_R^{Joint}$. Similarly, the second row (Alpha), reports the estimated proportions of funds with predictable alphas, $\pi_\alpha^-(j)$, $\widehat{\pi}_\alpha^+(j)$, and $\widehat{\pi}_\alpha^{Joint}$, obtained from the (bias-corrected) estimated slope coefficients, $\widehat{a}_{i,j}$, in Equation (2).

Overall, three insights stand out from Table II. First, there is ample evidence of predictability. In the entire population about 60.5% of the funds are predictable, while this proportion ranges from 31.1% (managed futures) to 83.7% (convertible arbitrage) across investment styles. Second, the time variation in performance is economically significant. Examining the cross-sectional distribution of the slope coefficients, $\widehat{b}_{i,j}$, we see that for 25% of the funds in the population, a one standard deviation decrease in the dividend yield, VIX, and aggregate flows causes an additional investment payoff of 43, 50, and 56 bp per month, respectively (5.2%, 6%, and 6.7% per year). Third, predictability is primarily attributable to alpha variation. Comparing the Return and Alpha rows reveals that, for most hedge fund styles, the proportions of funds exhibiting return and alpha predictability are almost identical (i.e., $\widehat{\pi}_R^- \approx \widehat{\pi}_\alpha^-$ and $\widehat{\pi}_R^+ \approx \widehat{\pi}_\alpha^+$).[13] This interpretation is consistent with AKNT who find that the benefits from exploiting return predictability mostly comes from the time variation in managerial skills (alpha). Sensitivity tests discussed below show that alpha predictability is robust to augmenting the Fung-Hsieh model with additional risk factors.

[13] This result is corroborated by evidence that the Fung-Hsieh benchmark factors are largely unpredictable. Unreported results show that only 5 out of the 28 estimated slope coefficients are significant (at the 10% level).

Please insert Table II here

Next, we turn to the analysis of the predictive ability of each macro variable on the cross-section of fund returns. First, we find that emerging market funds display the strongest positive relation with the default spread ($\widehat{\pi}_R^+$ =33.5%). Widening credit spreads typically coincide with flight to quality, which could in turn forecast higher future returns. A similar reasoning holds for the carry trade strategies in FX markets followed by global macro funds ($\widehat{\pi}_R^+ = 13.2\%$). Widening credit spreads can trigger the unwinding of carry trades, which leads to increasing future expected returns (e.g., Jylha and Suominen (2010), Christiansen, Ranaldo and Söderling (2011)).

A higher-than-average dividend yield strongly signals lower future performance for all categories ($\widehat{\pi}_R^-$ ranges from 14.8% to 37.8%), except managed futures. A natural explanation that is consistent with the business cycle interpretation of the dividend yield is leverage. In recessions, when the dividend yield is high, leverage availability from prime brokers is constrained, forcing hedge funds to reduce their exposures, thus generating low returns and alphas (see Ang, Gorovyy, and van Inwegen (2010)). This explains why we observe the opposite pattern for managed futures funds. Such funds encounter fewer leverage constraints as they trade in futures markets that are reasonably liquid over the business cycle. This liquidity allows managed futures funds to easily adjust their desired margin to equity ratio. Finally, our interpretation is also consistent with the fact that mutual fund returns are positively related with the dividend yield (Ferson and Qian (2004)). Contrary to hedge funds, mutual funds are not affected by leverage constraints and have a strong exposure to the stock market whose expected returns peak in recessions (e.g., Fama and French (1989)).

The vast majority of fund styles tend to perform poorly in times of higher market uncertainty. For instance, 39.0% of event-driven funds are negatively associated with the VIX, consistent with the higher deal failure rate in turbulent periods (e.g., Mitchel and Pulvino (2001)). Convertible arbitrage funds also display negative exposure ($\widehat{\pi}_R^- =$ 24.9%) as an increasing VIX may reduce opportunities of cheap volatility. Indeed, as shown by Choi et al. (2010), convertible arbitrage funds often exploit mispriced volatility in convertible bonds. Managed futures funds, in contrast, benefit from higher uncertainty ($\widehat{\pi}_R^+ = 16.7\%$). Indeed, managed futures funds (which include CTAs) tend do well following trend reversals which occur during periods of extreme VIX values. To illustrate, during the 2008 financial crisis, a Financial Times article observed that "*CTAs as an investment typically do best in periods of market chaos[...] they performed* *relatively well when implied volatility of equities rose on fears of Russian default and the Long Term Capital Management crash in 1998. A similar picture emerged in the run up to the Iraq war in 2002-2003, and now the credit crunch of 2008*".[14]

Finally, the strongest evidence of negative return predictability is found for aggregate flows. This flow-return relation confirms the finding of Naik, Ramadorai, and Stromquist (2007) obtained with hedge fund indices. They argue that capacity constraints, attributable to excessive inflows, hurt performance. By taking a fund-level perspective, we can determine the fraction of funds facing these constraints. We find that an increase in flows leads to a decrease in returns and alphas for 33.2% and 26.7% of the funds in the population, respectively. While these results highlight the negative impact of capacity constraints, they also reveal that many funds are not affected by this phenomenon.[15] Unsurprisingly, this effect is particularly strong for the crowded market of convertible arbitrage ($\widehat{\pi}_R^- = 44.7\%$). It is also strong for funds of funds, suggesting that the majority of them struggle to generate performance by deploying capital after large fund inflows.

Overall, the results shown in Table II are largely consistent with economic intuition. In particular, we find that the predictability pattern across funds largely reflects the performance impact of key hedge fund characteristics, such as leverage or capacity constraints. One important consequence of this consistency is the prominent "asymmetry" in the predictive ability of each macro variable. Specifically, when the value of a given predictor changes, the future fund returns tend to move in the same direction. For instance, while 22.2% of the funds exhibit a negative slope coefficient with respect to the dividend yield, only 4.1% have a positive exposure to it. As shown later, this asymmetry carries strong implications for deciphering the out-of-sample performance of the conditional strategies.

Our in-sample analysis examines return and alpha predictability at the monthly frequency. Arguably, liquidity constraints (such as lock-up periods) may prevent investors from rebalancing their fund portfolio at this time-horizon.[16] For hedge fund predictability to be exploitable out-of-sample, it must, therefore, be present at lower frequencies. As a first test, we examine predictability at a quarterly frequency. In unreported results, we still find ample evidence of predictability, suggesting that it could be exploited

[14] "One investment that loves chaos", Financial Times, 23 November 2008.

[15] We find that the rapid growth in the hedge fund industry has strengthened the role played by capacity constraints. While an increase in flows would reduce future alphas for only 6.5% of the funds between 1994 and 2000, this proportion has increased to 38.9% during the most recent period (2001-2007).

[16] Since liquidity constraints prevent investors from investing additional money into hedge funds, it may also explain why alphas are predictable in the first place. Baquero and Verbeek (2009) and Ding et al. (2009) raise a similar argument when they examine the performance of "smart money" strategies in hedge funds.

out-of-sample. We turn to this question next.

B Out-of-Sample Return Predictability

While we document ample evidence of in-sample predictability, institutional investors (such as funds of funds) typically encounter nontrivial impediments to exploiting hedge fund return predictability. First, predictable funds may have low unconditional mean, leading to a trade-off between unconditional and conditional performance. Second, the identity of predictable funds is unknown, and must be inferred from the data (estimation risk). Third, the predictive ability of the different macro variables can change over time (model misspecification). To address these concerns, we implement different conditional strategies that carefully incorporate real-world investment constraints and quantify the economic value of predictability.

First, we account for liquidity constraints by excluding closed funds as well as considering a one-year lock-up period (i.e., annual rebalancing). Second, there is a practical limit to the number of individual funds held by funds of funds. While data on such holdings is not publicly available, Lhabitant (2006) indicates that the typical number is about 40. As a result, we limit the minimum and maximum number of funds in the portfolio to 25 and 75, respectively. Third, investors typically do not invest in funds that are too small relative to their own size. As discussed in Ganshaw (2010), few institutional investors want to represent more than 10% of a fund's assets under management. We use this rule to set up a dynamic AuM cutoff equal to the minimum fund size such that a "typical" fund of funds does not breach this 10%-threshold.[17] The resulting cutoff rises from $12 million at the beginning to $63 million at the end of our sample. Contrary to the constant cutoffs used in previous studies (e.g., $20 million), our filter explicitly accounts for the growth in the hedge fund industry over time. Finally, we exclude funds of funds since institutional investors often focus on individual funds to avoid extra fees.

We consider the following trading strategies: (i) the unconditional portfolio which uses the unconditional t-statistic; (ii) the single-predictor strategy which ranks funds according to the conditional t-statistic obtained from each predictor (default spread, dividend yield, VIX, and aggregate flows); (iii) the multi-predictor strategy which uses all predictors simultaneously; (iv) the combination strategy which averages across the single-predictor t-statistics. The construction of the different portfolios proceeds as follows. At the end of each year, we estimate, for each strategy, the appropriate signal for each existing fund using past three-year returns, and form the top decile portfolio.

[17] The "typical" fund has an average size (as measured from the funds of funds AuM in our sample) and invests in 50 funds (the midpoint in our investment strategy).

This portfolio is kept during one year, after which the entire procedure is repeated.

Panel A of Table III reports the out-of-sample performance of all investment strategies between January 1997 and December 2007 (the period 1994-1996 is used for the initial estimation). First, we observe that the unconditional portfolio generates solid performance–the annual Fung-Hsieh alpha and Information Ratio (IR) are 5.8% and 2.4, respectively, thus easily beating the value- and equal-weighted hedge fund indices. This performance reflects the high signal accuracy of the unconditional mean as shown in Plot C of Figure 1, and is consistent with the results obtained by Kosowski, Naik, and Teo (2007), and Jagannathan, Malakhov, and Novikov (2010). Second, none of the single-predictor strategies outperforms the unconditional portfolio on a risk-adjusted basis (Information and Sharpe Ratios). Third, consistent with the previous literature (e.g., Avramov (2002) and Goyal and Welch (2008)), the multi-predictor strategy produces the worst performance ($IR = 1.5$) most likely due to severe estimation errors.

Remarkably, the combination strategy performs well. For one, Information and Sharpe Ratios, which amount to 2.7 and 1.9, respectively, are statistically significantly higher than their unconditional counterparts (at the 5% level). This superior performance translates into large economic gains over the entire period. We find that the wealth produced by the combination strategy accumulates steadily over time and reaches $3.74 (for each dollar invested in 1997), leading to an additional 50 cents of terminal wealth compared to the unconditional portfolio.[18]

Please insert Table III here

Importantly, the combination strategy does not introduce higher tail risk. The 1% and 5% Value-at-Risk in Table III equals -1.4% and -0.7% per month, respectively, and are thus the lowest among all competing strategies. From an investor perspective, the superior performance of the combination strategy is accompanied by several additional advantages displayed in Panel B. First, the strategy does not involve extensive (and possibly unrealistic) portfolio turnover–it exhibits the second lowest (66%) annual turnover of constituent funds. Second, the autocorrelation coefficients indicate that the superior performance of the combination strategy is not due to holding illiquid funds. The coefficients are comparable in magnitude to the other strategies, and are lower than the typical hedge fund autocorrelation coefficients (e.g., Lo (2002)). Third, performance is not driven by concentrated bets on specific investment categories. The highest weight,

[18] Repeating this analysis across the two largest investment categories (long-short equity and directional funds, which includes global macro, managed futures, and emerging markets), we confirm, in unreported results, the superior performance of the combination strategy.

invested in long-short equity funds, is only equal to 11.8% on average over the period. Finally, Panel C of Table III shows that the combination strategy behaves like a pure alpha strategy, as its exposures to the Fung-Hsieh risk factors are very low.

Comparing our results with the performance of the Bayesian strategies examined in AKNT, we find that the combination strategy generates a higher risk-adjusted performance (Sharpe and Information Ratios). In addition, because the latter invests in a larger number of funds, it addresses the concern raised by AKNT about the high concentration of their portfolios. More importantly, the conditional strategies considered here are extremely simple as the investment mechanism boils down to considering two portfolios only, the unconditional and slope portfolios (see Equation (5)). Thus, our proposed setup allows for a deep understanding of the drivers of out-of-sample performance. Specifically, we show below that there exist strong links between in-sample and out-of-sample return predictability.

C The Relation between In- and Out-of-Sample Predictability

C.1 Explaining the Performance of Single-Predictor Strategies

While our previous analysis reveals that none of the single-predictor strategies consistently beat the unconditional portfolio, it does not explain when and why these strategies tend to underperform. To address this question, we focus on periods when the predictor value departs from its long run mean. At these specific times, the single-predictor strategy moves from the unconditional to the slope portfolio. We conjecture that a key driver of performance should be the ability of the slope portfolio to detect the (truly) predictable funds from the data.

Consider, for instance, the default spread. In Table IV, we group the values of the default spread, $z_{j,t}$, observed at each rebalancing date into quintiles, and examine the strategy allocation when $z_{j,t}$ is either far below (bottom quintile) or above (top quintile) its long run mean. As expected, Panel A shows that when the default spread takes on extreme values, the conditional strategy has a large exposure to the slope portfolio. For instance, when $z_{j,t}$ is in the top quintile, 77.2% of the funds chosen by the strategy are common to those included in the slope portfolio ($\%_{slope} = 77.2\%$).

But more importantly, the quality of the predictive information is very different depending on the sign of $z_{j,t}$. Looking at the cross-fund average slope t-statistic, denoted by $t(\widehat{b}_j)$, we observe that it is quite low when $z_{j,t}$ is negative ($t(\widehat{b}_j) = 0.96$), and very high when $z_{j,t}$ is positive ($t(\widehat{b}_j) = 2.03$). This reflects the strong "asymmetry" documented in-sample. Since there are a lot more funds with a positive exposure to the default spread in the population (in Panel A of Table II, $\pi_R^+ = 14.5\%$ versus $\pi_R^- = 1.6\%$), it should be much easier to identify these predictable funds from the data when $z_{j,t}$ is positive. As suggested, Panel B reveals that the out-of-sample performance of the strategy is much higher after observing a high default spread at the rebalancing date–the Fung-Hsieh annual alpha is equal to 14.8% (as opposed to 6.0% when the default spread is low).

The same analysis applies to the dividend yield, VIX, and aggregate flows. In each case, Panel A documents a strong asymmetry in the quality of forecasting information, which matches the in-sample asymmetry observed in Table II. This, in turn, leads to a strong asymmetry in out-of-sample performance, as shown in Panel B.

Please insert Table IV here

Figure 2 provides additional evidence on the relation between the predictor value and out-of-sample performance. In each plot, we show the evolution of the predictor value along with the difference in Information Ratio between the single-predictor strategy and the unconditional portfolio. The results confirm those in Table IV. To illustrate, the performance of the dividend yield strategy goes up in times when the dividend yield is below average, consistent with the negative exposure to the dividend yield documented in-sample ($\pi_R^- = 22.2\%$, as opposed to $\pi_R^+ = 4.1\%$). Overall, we find that the return predictability documented in-sample largely explains when and why the single-predictor strategies outperform.

In this paper, we examine predictability from a multi-asset perspective. Specifically, we measure in-sample predictability with the predictor's ability to forecast cross-sectional fund returns, and out-of-sample predictability with the strategy's ability to select outperforming funds in this cross-section. Using these new predictability metrics is essential to unveil the relation between in- and out-of-sample return predictability. Indeed, as clearly shown in the previous literature (e.g., Bossaerts and Hillion (1999), Goyal and Welch (2008)), there is virtually no relation between these two notions when one considers each asset in isolation.

Please insert Figure 2 here

C.2 Explaining the Performance of the Combination Strategy

In essence, taking large positions in the slope portfolio hurts the performance of the single-predictor strategy in times when the predictor's forecast accuracy is poor. How does the combination strategy overcome this difficulty? First and consistent with Equation (6), it takes a substantial position in the unconditional portfolio. To illustrate, Figure 3 shows the fraction of funds chosen by each conditional strategy that are common to those held by the unconditional portfolio. While there are large variations for both single- and multi-predictor strategies, the proportion associated with the combination strategy is stable around 80%.

While Rapach, Strauss, and Zhou (2010) highlight the benefits of shrinkage in a single-asset environment, we argue that the combination approach is even more attractive in the presence of multiple assets because of the trade-off between unconditional and predictable performance. Indeed, by investing in the slope portfolio at the wrong time, the investor picks up funds exhibiting low return predictability, and, in addition, fails to capture the relatively high performance produced by the unconditional portfolio.

Please insert Figure 3 here

Second, the active bets taken by the combination strategies portfolio produce a positive performance that is not subject to the asymmetry described earlier. To see this, we can write the return of the combination strategy, r_{t+1}^{com}, as the return of the unconditional portfolio, r_{t+1}^{u}, plus the return of an investment in a zero-cost long-short portfolio, r_{t+1}^{ls}:

$$r_{t+1}^{com} = r_{t+1}^{u} + w_t \cdot r_{t+1}^{ls} = r_{t+1}^{u} + w_t \cdot (r_{t+1}^{l} - r_{t+1}^{s}), \tag{9}$$

where r_{t+1}^{l} is the return of a long portfolio that contains those funds selected by the combination strategy, while r_{t+1}^{s} is the return of a short portfolio consisting of funds that are only selected by the unconditional strategy. Finally, w_t is the weight invested in this long-short position, which, from Figure 5, is around 20%. For each predictor, Table V displays the annual out-of-sample performance of the long and short portfolios, r_t^l and r_t^s, when the predictor value, $z_{j,t}$, is far below (bottom quintile) or above (top quintile) its long run mean. Contrary to single-predictor strategy, there is no asymmetric performance because the long portfolio delivers superior performance in the two quintiles. For instance, we find that the Fung-Hsieh alpha differential against the unconditional portfolio, $\widehat{\alpha} - \widehat{\alpha}_U$, is equal to 5.3% per year, even when the default spread has the "wrong" value, i.e., when it is below average ($z_{j,t} < 0$). By combining across predictors, the long portfolio is able to generate a high performance that is orthogonal to that of the slope portfolios. Indeed, Panel A shows that the proportion of funds that are common to any given slope portfolio is at most equal to 14%. By the same token, Panel B shows that the combination strategy also excludes funds that are expected to underperform.[19]

Please insert Table V here

D The 2008 Financial Crisis

The recent financial crisis featured one of the most extreme changes in market conditions and, as such, raises specific questions about the dynamics of hedge fund returns. First, given the strong impact that extreme predictor values have on fund selection, we examine how performance changes during 2008. Panel A of Table VI reports the out-of-sample performance of the unconditional and conditional strategies (single-, multi-predictor, and combination) between January 1997 and December 2008. Even including the crisis, the combination strategy still achieves a reasonably strong performance. Its Information Ratio is not only the highest (IR =1.9), but is also statistically significantly higher than that of the unconditional portfolio (the associated p-value is below 1%). In general, all strategies have been hit quite hard during the crisis. For instance, the cumulative loss during the final quarter of 2008 amounts to 14.1% for the unconditional portfolio, and to 12.3% and 14.1% for the default spread and aggregate flows strategies, respectively. There is one noticeable exception. The conditional strategy based on the VIX yields the highest Sharpe Ratio (SR=1.4), and resists remarkably well during the final quarter of 2008 (with only a 3.1% cumulative loss).

Please insert Table VI here

Second, the extreme fluctuations of the predictor values may have been accompanied by structural breaks in the predictive regressions. These breaks may in turn explain why the single-predictor strategies perform very differently during the crisis. In Panel B of Table VI, we find as expected that the December 2007 value of each predictors is very different from its long-run average, making the strategies very sensitive to the forecasting accuracy of the respective predictors (i.e., the fraction $\%_{slope}$ ranges from 48.0% to 76%). To evaluate this ability during the crisis, we compute the hit ratio that determines the proportion of months when the portfolio predictable component, $\widehat{b}_{j,t} \cdot z_{j,t}$, is positive, where $z_{j,t}$ is the predictor value at the start of each month, and $\widehat{b}_{j,t}$ is the average slope coefficient among the funds included in the slope portfolio ($\widehat{b}_{j,t}$ is estimated with the 36

[19] As an additional test of the combination strategy's ability to detect predictable funds, we examine the out-of-sample forecasting ability of the monthly long-short portfolio returns, r^{ls}_{t+1}. These unreported results confirm that combined forecasts, averaged across the four predictors, achieve a lower Mean Squared Prediction Error (MSPE) than the historical mean.

most recent monthly observations). The results suggest that the VIX strategy performs well in 2008 because its predictive power is much more stable–its hit ratio is extremely high (83.3%). On the contrary, the hit ratios of the default spread and the dividend yield equal 25.0% and 16.6%, respectively, and are much lower than those computed over the period 1997-2007 (87.5% and 83.3%, respectively). These low hit ratios are not due to a change in sign of the predictor value–Panel B shows that in 2008, the value of the default spread or the dividend yield remains constantly above its historical average (i.e., $z_j z_{j,t} > 0$ for all months). Overall, our results suggests that the recent crisis may have caused important structural breaks that mostly affected the default spread and the dividend yield, but not the VIX.

Finally, a key issue raised during the crisis is the additional liquidity costs borne by investors willing to reshuffle their hedge fund portfolios. To prevent massive outflows, many hedge funds reacted by lengthening redemption notice periods, erecting gates, or creating side-pockets. We estimate these liquidity costs by computing the performance of the different conditional strategies between January 1997 and December 2008 if investors had been allowed to rebalance their portfolio monthly during 2008 (using all information available at the start of the month). The results in Panel C show that monthly rebalancing leads to a large improvement in performance compared to annual rebalancing (Panel A). For instance, the increase in annual alpha (Δ) is equal to 1.5%, 2.4%, and 1.7% for the unconditional, aggregate flows, and combination strategies, respectively. Based on this metric, the liquidity constraints carried considerable costs to hedge fund investors during the crisis.

E Sensitivity Tests

So far our results indicate that the combination strategy generates higher risk-adjusted performance than all other strategies. To determine whether this conclusion is robust to alternative specifications, we perform a range of sensitivity checks reported in Table VII. First, our conclusions are robust to reducing the maximum number of funds from 75 to 50, as well as to removing this upper bound (i.e., holding the top decile portfolio even when it contains many funds). Second, repeating the analysis to include small funds (rather than imposing the AuM cutoff) leaves the relative performance of the combination strategy nearly unchanged.

In our baseline specification, we assume that when a fund stops reporting returns, its capital allocation is invested at the riskless rate. Therefore, we avoid look-ahead bias since we do not condition on a fund being alive during the entire year. However, funds generally disappear from the database because they are liquidated. To address this issue, we penalize any missing monthly observation with a -25% return (as in De Los Rios and Garcia (2010)), after which the remaining funds are invested in the riskfree asset. In this case, the relative performance of the combination strategy slightly improves.

Most hedge fund databases receive hedge fund returns with a delay as most funds report NAV and return performance several weeks after month-end. Although large hedge fund investors may obtain return and NAV estimates from a subset of hedge funds directly, the vast majority of investors rely on commercially available data bases like ours. Examining the economic value of predictability when reporting lags are explicitly taken into account, we find that the combination strategy still significantly outperforms.

One important constraint is that of redemption notice periods–an investor who wishes to rebalance his hedge fund portfolio in December may have to give notice to the fund, typically three months in advance. To address this issue, we carry out a robustness test in which the investor has to decide, based on the information observed at the end of September, which funds to hold at December end. We find that the superior performance of the combination is robust to this change.

We also document that the performance of the combination strategy that based on the t-statistic of the conditional alpha (as opposed to total returns) is even better. This is consistent with our previous discussion that most in-sample return predictability is driven by alpha predictability. However, focusing on alpha predictability is more sensitive to the potential bias caused by omitted benchmark assets, as we use the same model to form the portfolio and evaluate subsequent performance (e.g., Carhart (1997)).

Please insert Table VII

Finally, to guard against the possibility of omitted benchmarks, we examine whether the alpha and Information Ratios computed using the Fung-Hsieh model change under alternative specifications. We consider the four-factor model (market, size, book-to-market, and momentum factors) and extended versions of the Fung-Hsieh model that include the Pastor and Stambaugh (2003) liquidity factor, the emerging market portfolio, and an additional equity straddle. We find in unreported results that the superior performance of the combination strategy remains unchanged.

V Conclusion

This paper develops and applies a unified methodological framework to assess both in-sample and out-of-sample hedge fund return predictability. Using a comprehensive sample of individual funds, we identify the fraction of funds in the population having future returns that are (i) negatively related; (ii) unrelated; or (iii) positively related to the different macro variables (default spread, dividend yield, VIX, and aggregate flows). To measure out-of-sample predictability, we examine the performance of very simple conditional strategies that incorporate several real-world investment constraints faced by institutional investors.

The overall evidence documented here makes several contributions to the literature on hedge funds and return predictability. First, we provide a detailed analysis of the time-variation of individual fund performance across changing market conditions. We find that return predictability is widespread and follows a pattern across investment catgeories that is largely consistent with economic rationale. Second, we show that a conditional strategy that combines forecasts across each macro variable is able to deliver superior performance, even during the recent financial crisis. By diversifying across forecasts, this combination strategy avoids making a poor fund selection in times when return forecasts are not sufficiently accurate. Finally, our unified approach allows for a detailed analysis of the drivers of out-of-sample performance. In our multi-fund setting, we show that the return predictability documented in-sample is critical in explaining when and why conditional strategies outperform out-of-sample.

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VI Appendix

A Estimating the Slope Coefficients

A.1 Return Predictability

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

$$\begin{aligned} r_{i,t+1} &= b_{i,0} + b_i' Z_t + u_{i,t+1}, \\ Z_{t+1} &= \theta + \Phi Z_t + v_{t+1}, \qquad t = 2, ..., T+1, \end{aligned} \tag{A1}$$

where $r_{i,t+1}$ the fund excess return (over the riskfree rate) between t and $t+1$, Z_t is the J-vector of predictors observed at time t, $b_{i,0}$ is the intercept, $b_i = [b_{i,1}, ..., b_{i,J}]'$ is the J-vector of slope coefficients, and Φ is the $J \times J$ companion matrix of the VAR(1). We denote by $u_{i,t+1}$ the fund innovation term and by v_{t+1} the J-vector of predictor innovations between time t and $t+1$. We assume that $u_{i,t+1} = E(u_{i,t+1} | v_{t+1}) + e_{i,t+1} = \phi_i' v_{t+1} + e_{i,t+1}$, where ϕ_i is the J-vector of innovation coefficients, and $e_{i,t+1}$ is the fund residual term (orthogonal to Z_t and v_{t+1}). While v_{t+1} is modelled as an i.i.d. process, we allow $e_{i,t+1}$ to be autocorrelated to account for potential illiquidity, as explained in Appendix B.

To construct a proxy, v_{t+1}^c, for the unobserved J-vector v_{t+1}, we follow the procedure initially described by Amihud and Hurvich (2004) and further developed by Amihud, Hurvich, and Wang (2008; AHW hereafter). We describe the main steps of the estimation procedure, and refer to them for further detail. First, we compute the VAR(1) estimates $\widehat{\theta}$ and $\widehat{\Phi}$. Based on these estimates, we obtain the time-series of estimated innovation vector, $\widehat{v}_{t+1}$, from which we compute the $J \times J$ innovation covariance matrix, denoted by $\widehat{\Sigma}_v$. Second, we use $\widehat{\theta}$, $\widehat{\Phi}$, and $\widehat{\Sigma}_v$ to correct for the small-sample bias in $\widehat{\Phi}$ using the analytical formula proposed by Nicholls and Pope (1988):

$$\widehat{bias}(\widehat{\Phi}) = -\frac{1}{T}\widehat{\Sigma}_v \left[\left(I_J - \widehat{\Phi}'\right)^{-1} + \widehat{\Phi}' \left(I_J - \widehat{\Phi}'^2\right)^{-1} + \sum_{j=1}^{J} \lambda_j \left(I_J - \lambda_j \widehat{\Phi}'\right)^{-1} \right] \widehat{\Sigma}_Z^{-1}, \tag{A2}$$

where T is the number of observations, I_J is a $J \times J$ identity matrix, and λ_j denotes the j^{th} eigenvalue of $\widehat{\Phi}'$, and $\widehat{\Sigma}_Z$ is the $J \times J$ covariance matrix of Z_t computed using the following formula: $vec(\Sigma_v) = (I_{J^2} - A)vec(\Sigma_Z)$, where vec is the vec operator, I_{J^2} is a $J^2 \times J^2$ identity matrix, and $A = (\Phi \otimes \Phi)$ (see Hamilton (1994), p. 265). The bias formula , $\widehat{bias}(\widehat{\Phi})$, is estimated iteratively. In each iteration k ($k = 2, ..., K$), we use the following updating scheme: $\widehat{\Phi}_{(k)} = \widehat{\Phi}_{(k-1)} - \widehat{bias}(\widehat{\Phi})_{(k)}$ and $\widehat{\theta}_{(k)} = \left(I - \widehat{\Phi}_{(k)}\right)\overline{Z}$, where $\overline{Z}$ denotes the sample mean, and $\widehat{\Sigma}_{\upsilon(k)}$ is obtained using the updated estimates, $\widehat{\Phi}_{(k)}$ and $\widehat{\theta}_{(k)}$. As in AHW, the number of iterations, K, is set equal to 10. Third, we use the final bias-corrected VAR(1) estimates, $\widehat{\theta}^c$ and $\widehat{\Phi}^c$, to construct the proxy, υ_t^c:

$$\upsilon_t^c = Z_{t+1} - \widehat{\theta}^c + \widehat{\Phi}^c Z_t, \qquad t = 2, ..., T+1. \tag{A3}$$

To compute the J-vector of bias-corrected estimated slope coefficients, $\widehat{b}_i$, we replace υ_t with υ_t^c in Equation (7), and regress the fund return, $r_{i,t+1}$, on an augmented vector x_t including $2{\cdot}J + 1$ explanatory variables: $x_t = [1, Z_t', \upsilon_{t+1}^{c\prime}]'$. Replacing $u_{i,t+1}$ with $\phi_i'\upsilon_{t+1} + e_{i,t+1}$ in Equation (A1) and υ_{t+1} with $\upsilon_{t+1}^c + (\widehat{\theta}^c - \theta) + \left(\widehat{\Phi}^c - \Phi\right) Z_t$, we can determine the remaining bias in the J-vector $\widehat{b}_i$: $bias(\widehat{b}_i) = E\left(\widehat{\Phi}^c - \Phi\right)'\phi_i$. We show that $\widehat{b}_i$ is nearly unbiased since the estimated companion matrix, $\widehat{\Phi}^c$, is corrected for the small sample bias and gets very close to the true value, Φ.[20]

A.2 Alpha Predictability

AHW focus on time series predictive regressions. Here, we extend their approach to control for small-sample bias in the asset pricing regression with time varying alpha formulated in Equation (2):

$$r_{i,t+1} = a_{i,0} + a_i' Z_t + \beta_i' f_{t+1} + \epsilon_{i,t+1}, \tag{A4}$$

where $a_{i,0}$ is the intercept, $a_i = [a_{i,1}, ..., a_{i,J}]'$ is the J-vector of alpha slope coefficients, and β_i the K-vector of fund exposure to the K risk factors, f_{t+1}, and $\epsilon_{i,t+1}$ is the new innovation term (orthogonal to Z_t and F_{t+1}). Projecting the J-vector of predictor innovation, υ_{t+1}, onto the space spanned by f_{t+1}, we obtain a new innovation vector denoted by ω_{t+1}, i.e., $\omega_{t+1} = \upsilon_{t+1} - q_\upsilon - Q_\upsilon f_{t+1}$, where q_υ is a J-vector and Q_υ a $J \times K$ coefficient matrix. As in Equation (A1), the new innovation terms are correlated: $\epsilon_{i,t+1} = E\left(\epsilon_{i,t+1} \left| \omega_{t+1}\right.\right) + \varrho_{i,t+1} = \psi_i'\omega_{t+1} + \varrho_{i,t+1}$, where ψ_i is the J-vector of innovation coefficients, and $\varrho_{i,t+1}$ is the fund residual term (orthogonal to Z_t, f_{t+1}, and ω_{t+1}).

Similar to Equation (7), the small-sample bias in the J-vector of OLS-estimated alpha slope coefficients, $\widehat{a}_i^{ols}$, can be eliminated if we include the J-vector ω_{t+1} as an

[20] As shown by Nicholls and Pope (1988), the estimated bias, $\widehat{bias}(\widehat{\Phi})$, shown in Equation (A2) is very close from the true (but unobservable) bias, $bias(\widehat{\Phi})$, since $bias(\widehat{\Phi}) = \widehat{bias}(\widehat{\Phi}) + O(T^{-\frac{3}{2}})$.

additional vector of explanatory variables, i.e.,

$$r_{i,t+1} = a_{i,0} + a_i' Z_t + \beta_i' f_{t+1} + \psi_i' \omega_{t+1} + \varrho_{i,t+1}, \tag{A5}$$

because the orthogonality condition holds, i.e., $E(\varrho_i | X) = 0$, where $\varrho_i = [\varrho_{i,1}, ..., \varrho_{i,T+1}]'$, $X = [x_1, ..., x_{T+1}]'$, and $x_t = [Z_{t-1}', \upsilon_t', f_t']'$. Of course, we cannot observe the true innovation vector thus we have to find a proxy for it denoted by υ_{t+1}^c. To proxy for the unobservable vector, ω_{t+1}, we take the J-vector of innovation, υ_{t+1}^c, computed in Equation (A3) and regress it on the factor returns, f_{t+1}, and a constant to obtain

$$\omega_{t+1}^c = \upsilon_{t+1}^c - \widehat{q}_\upsilon - \widehat{Q}_\upsilon f_{t+1}. \tag{A6}$$

To compute the J-vector of bias-corrected estimated alpha slope coefficients, $\widehat{a}_i$, we replace ω_{t+1} with ω_{t+1}^c in Equation (A5), and regress the fund return, $r_{i,t+1}$, on an augmented vector x_t including $2J+K+1$ explanatory variables variables: $x_t = [1, Z_t', f_{t+1}', \omega_{t+1}^{c\prime}]'$. We can replace $\epsilon_{i,t+1}$ with $\psi_i' \omega_{t+1} + \varrho_{i,t+1}$ in Equation (A4), where

$$\begin{aligned} \omega_{t+1} &= \upsilon_{t+1} - q_{\upsilon,0} - Q_\upsilon f_{t+1} \\ &= \omega_{t+1}^c + (\widehat{\theta}^c - \theta_j) + \left(\widehat{\Phi}^c - \Phi\right) Z_t + (\widehat{q}_\upsilon - q_\upsilon) + \left(\widehat{Q}_\upsilon - Q_\upsilon\right)' f_{t+1}, \end{aligned} \tag{A7}$$

to get an expression for the remaining bias that is similar to the one obtained for the return predictive regression, i.e., $bias(\widehat{a}_i) = E\left(\widehat{\Phi}^c - \Phi\right)' \psi_i$.

A.3 Quarterly Return Predictability

Here, we extend the AHW approach to assess hedge fund predictability at the quarterly horizon. Let us denote by $r_{i,t:t+1}$, $r_{i,t+1:t+2}$, and $r_{i,t+2:t+3}$ the (excess) return of fund i between time t and $t+1$, $t+1$ and $t+2$, and $t+2$ and $t+3$, respectively. Based on Equation (A1), we can write:

$$\begin{aligned} r_{i,t:t+1} &= b_{i,0} + b_i' Z_t + \phi_i' \upsilon_{t+1} + e_{i,t+1}, \\ r_{i,t+1:t+2} &= b_{i,0} + b_i' Z_{t+1} + \phi_i' \upsilon_{t+2} + e_{i,t+2} \\ &= b_{i,0} + b_i'(\theta + \Phi Z_t + \upsilon_{t+1}) + \phi_i' \upsilon_{t+2} + e_{i,t+2}, \\ r_{i,t+2:t+3} &= b_{i,0} + b_i' Z_{t+2} + \phi_i' \upsilon_{t+3} + e_{i,t+3}, \\ & \quad b_{i,0} + b_i'(\theta + \Phi(\theta + \Phi Z_t + \upsilon_{t+1}) + \upsilon_{t+2}) + \phi_i' \upsilon_{t+3} + e_{i,t+3}. \end{aligned} \tag{A8}$$

Ignoring compounding effects, the monthly growth rate of fund i over the next quarter, denoted by $r^q_{i,t+3}$, is equal to $\frac{1}{3}(r_{i,t:t+1}+r_{i,t+1:t+2}+r_{i,t+2:t+3})$. After grouping the different terms in Equation (A8), we can write $r^q_{i,t+3}$ as

$$r^q_{i,t+3} = b^q_{i,0} + b^{q\prime}_i Z_t + \phi^{q\prime}_{i,1}\upsilon_{t+1} + \phi^{q\prime}_{i,2}\upsilon_{t+2} + \phi^{q\prime}_{i,2}\upsilon_{t+3} + e^q_{i,t+3}, \tag{A9}$$

where $b^q_{i,0} = \frac{1}{3}(3b_{i,0} + 2b_i'\theta + 2b_i'\Phi\theta)$, $b^q_i = \frac{1}{3}(b_i + b_i\Phi' + b_i\Phi^{2\prime})$, $\phi^q_{i,1} = \frac{1}{3}(\phi_i + b_i + b_i\Phi')$, $\phi^q_{i,2} = \frac{1}{3}(\phi_i + b_i)$, $\phi^q_{i,3} = \frac{1}{3}\phi_i$, and $e^q_{i,t+3} = \frac{1}{3}(e_{i,t+1} + e_{i,t+2} + e_{i,t+3})$. Equation (A9) reveals that we need to include three lags of the J-vector of innovation, υ_{t+1}, υ_{t+2}, and υ_{t+3}, to control for small sample bias at a quarterly horizon. To apply the method of Amihud, Hurvich, and Wang, we use the proxy υ^c_{t+1} computed in Equation (A3). Then, we construct $r^q_{i,t:t+3}$ using overlapping monthly observations and regress it on the $4 \cdot J + 1$-vector, x_t, of explanatory variables variables: $x_t = [1, Z_t', \upsilon^{c\prime}_{t+1}, \upsilon^{c\prime}_{t+2}, \upsilon^{c\prime}_{t+3}]$ to obtain the J-vector of bias-corrected estimated slope coefficients, $\widehat{b}^q_i$ at the quarterly horizon.

B Estimating the Slope Coefficient t-statistic (and p-values)

We extend the approach of AHW to incorporate hedge fund illiquidity when computing the variance of the estimated bias-corrected slope coefficient, $\widehat{b}_{i,j}$, associated with each predictor j ($j = 1, ..., J$).[21] Following AHW, we can write the estimated variance of $\widehat{b}_{i,j}$ as

$$\widehat{var}(\widehat{b}_{i,j}) = \sum_{i=1}^{J}\sum_{k=1}^{J} \widehat{\phi}_{i,j}\widehat{\phi}_{k,j}\widehat{cov}(\widehat{\rho}_{ij}, \widehat{\rho}_{kj}) + \widehat{var}_{aug}(\widehat{b}_{i,j}), \tag{A10}$$

where $\widehat{\rho}_{i,j}$ denotes the i^{th} row-j^{th} column element of the estimated companion matrix, $\widehat{\Phi}^c$, and $\widehat{\phi}_{i,j}$ is the j^{th} element of the J-vector of estimated innovation coefficients, $\widehat{\phi}_i$. The terms $\widehat{cov}(\widehat{\rho}_{ij}, \widehat{\rho}_{kj})$ are read from the estimated covariance matrix of the VAR(1). Finally, $\widehat{var}_{aug}(\widehat{b}_{i,j})$ is the $(j+1)$ diagonal element of the $(2J+1)\times(2J+1)$ estimated covariance matrix of the augmented regression, $\widehat{V}_{aug}(\widehat{b}_{i,0}, \widehat{b}_i, \widehat{\phi}_i) = (X'X)^{-1}\left(X'\widehat{V}_iX\right)^{-1}(X'X)^{-1}$, where $X_{(T\times(2\cdot J+1))} = [x_1, ..., x_T]'$, $x_1 = [1, Z_1', \upsilon^{c\prime}_2]'$, and $\widehat{V}_i$ is the $T \times T$ estimated covariance matrix of the fund residual vector $e_i = [e_{i,2}, ..., e_{i,T+1}]'$.

To account for autocorrelation caused by potential illiquidity, we estimate V_i using an AR specification. Based on empirical evidence (discussed in Section II.C.2 of the

[21] While our presentation focuses on return predictability, the procedure used to estimate (i) the slope coefficient t-statistic (ii) the proportions of funds with predictable returns; (iii) the conditional t-statistic is the same for alpha predictability.

paper), we use a two-month lag, i.e.,

$$e_{i,t+1} = \rho_{i,1}e_{i,t} + \rho_{i,2}e_{i,t-1} + \xi_{i,t+1}. \tag{A11}$$

After estimating the coefficients in Equation (A11) from fund i estimated innovation, $\widehat{e}_{i,t+1}$, we compute $\widehat{V}_i$ as $\widehat{var}(\widehat{\xi}_{i,t+1})\left(\widehat{\Psi}_i'\widehat{\Psi}_i\right)^{-1}$, where $\widehat{\Psi}_i$ is defined as

$$\begin{bmatrix} \left(\frac{(1+\widehat{\rho}_{i,2})[(1-\widehat{\rho}_{i,2}^2)-\widehat{\rho}_{i,1}^2]}{1-\widehat{\rho}_{i,2}}\right)^{\frac{1}{2}} & 0 & 0 & 0 & ... & 0 & 0 & 0 \\ \frac{\widehat{\rho}_{i,1}(1-\widehat{\rho}_{i,1}^2)^{\frac{1}{2}}}{1-\widehat{\rho}_{i,2}} & (1-\widehat{\rho}_{i,2}^2)^{\frac{1}{2}} & 0 & 0 & ... & 0 & 0 & 0 \\ -\widehat{\rho}_{i,2} & -\widehat{\rho}_{i,1} & 1 & & ... & 0 & 0 & 0 \\ ... & ... & ... & ... & ... & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & ... & -\widehat{\rho}_{i,2} & -\widehat{\rho}_{i,1} & 1 \end{bmatrix}, \tag{A12}$$

and $\widehat{var}(\widehat{\xi}_{i,t+1})$ is the estimated variance of the innovation term in Equation (A11) (see Greene (2000)).

C Estimating the Proportions of Unpredictable and Predictable Funds

For each predictor j ($j = 1, ..., J$), we estimate the proportions of funds with predictable returns, $\pi_R^-(j)$, and $\pi_R^+(j)$, using the method proposed by Barras, Scaillet, and Wermers (2010; BSW). The only required input is the M-vector of p-values associated with the estimated slope coefficient, $\widehat{b}_{i,j}$ of each fund i in the population ($i = 1, ..., M$). To this end, we use the estimated variance in Equation (A10), and compute the slope t-statistic of each fund i as $t(\widehat{b}_{i,j}) = \widehat{b}_{i,j}/\widehat{var}(\widehat{b}_{i,j})^{\frac{1}{2}}$. Then, we follow AHW and compute the fund p-value as $p(\widehat{b}_{i,j}) = 2(1 - F_N(\left|t(\widehat{b}_{i,j})\right|))$, where F_N is the cumulative function of a normal distribution.

We also compute the estimated proportion of predictable funds, $\widehat{\pi}_R^{Joint}$, when all predictors are considered simultaneously (shown in the final column of Table II). To this end, we compute the Wald test suggested by AHW: $w(\widehat{b}_i) = \widehat{b}_i'\widehat{V}\left(\widehat{b}_i\right)^{-1}\widehat{b}_i$, where $\widehat{V}\left(\widehat{b}_i\right)$ is the $J \times J$ estimated covariance matrix of the J-vector $\widehat{b}_i$. While the diagonal elements of $\widehat{V}\left(\widehat{b}_i\right)$ are given by Equation (A10), AHW show that a similar expression holds for the covariance terms, $\widehat{cov}(\widehat{b}_{i,j}, \widehat{b}_{i,k})$. The p-value associated with this joint test is computed as $p(\widehat{b}_i) = 1 - F_N(w(\widehat{b}_i))$, where F_N is the cumulative function of a χ^2 distribution with J degrees of freedom.

D Estimating the Conditional t-statistic

As discussed in Section B.1, the conditional strategy selects funds with the highest conditional t-statistic, $t(\widehat{\mu}_{i,t}) = \widehat{\mu}_{i,t}/\widehat{var}(\widehat{\mu}_{i,t})^{\frac{1}{2}}$, where $\widehat{\mu}_{i,t}$ is the fund estimated conditional mean and $\widehat{var}(\widehat{\mu}_{i,t})$ denotes its estimated variance (see Equation (4)). In this section, we explain how to compute the conditional t-statistic both in the single- and multi-predictor case.

In the case of the single-predictor strategy that uses predictor j ($j = 1, ..., J$), we can write $\widehat{\mu}_{i,t}(j)$ and $\widehat{var}(\widehat{\mu}_{i,t}(j))^{\frac{1}{2}}$ as

$$\widehat{\mu}_{i,t}(j) = \widehat{b}_{i,0} + \widehat{b}_{i,j} Z_{j,t}, \qquad \widehat{var}(\widehat{\mu}_{i,t}(j)) = X_t' \widehat{V}\left(\widehat{b}_{i,0}, \widehat{b}_{i,j}\right) X_t, \tag{A16}$$

where $\widehat{b}_{i,0}$ and $\widehat{b}_{i,j}$ denote the bias-corrected estimated intercept and slope coefficient, $Z_{j,t}$ is the predictor value at time t, $X_t = [1, Z_{j,t}]'$, and $\widehat{V}\left(\widehat{b}_{i,0}, \widehat{b}_{i,j}\right)$ is the 2×2 estimated covariance matrix of the regression coefficients. To estimate $\widehat{b}_{i,0}$ and $\widehat{b}_{i,j}$, we use the simplified approach proposed by Amihud and Hurvich (2004, AH hereafter) for single-predictor regressions. First, we estimate the AR(1) model for predictor $j : Z_{j,t+1} = \widehat{\theta}_j + \widehat{\rho}_j Z_{j,t} + \widehat{\upsilon}_{j,t+1}$. Second, we replace the unobservable innovation term, $\upsilon_{j,t+1}$, 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 suggested by AH. Specifically,

$$\begin{aligned} \widehat{\rho}^c_j &= \widehat{\rho}_j + (1 + 3\widehat{\rho}_j)/T + 3(1 + 3\widehat{\rho}_j)/T^2, \\ \widehat{\theta}^c_j &= 1/(1 - \widehat{\rho}_j)\overline{Z}_j, \end{aligned} \tag{A17}$$

where T denotes the number of return observations, and $\overline{Z}_j$ denotes the sample mean. Third, we regress the hedge fund return, $r_{i,t+1}$, on the augmented vector x_t including 3 explanatory variables, $x_t = [1, Z_{j,t}, \upsilon^c_{j,t+1}]'$.

To compute $\widehat{V}\left(\widehat{b}_{i,0}, \widehat{b}_{i,j}\right)$ we follow AH and write the estimated variances of $\widehat{b}_{i,0}$ and $\widehat{b}_{i,j}$, as well as their estimated covariance as

$$\begin{aligned} \widehat{var}(\widehat{b}_{i,0}) &= \widehat{\phi}^2_{i,j} \widehat{var}(\widehat{\theta}^c_j) + \widehat{var}_{aug}(\widehat{b}_{i,0}), \\ \widehat{var}(\widehat{b}_{i,j}) &= \widehat{\phi}^2_{i,j} \widehat{var}(\widehat{\rho}^c_j) + \widehat{var}_{aug}(\widehat{b}_{i,j}) \\ \widehat{cov}(\widehat{b}_{i,0}, \widehat{b}_{i,j}) &= \widehat{\phi}^2_{i,j} \widehat{cov}(\widehat{\theta}^c_j, \widehat{\rho}^c_j) + \widehat{cov}_{aug}(\widehat{b}_{i,0}, \widehat{b}_{i,j}), \end{aligned} \tag{A18}$$

where $\widehat{var}(\widehat{\theta}^c_j)$, $\widehat{var}(\widehat{\rho}^c_j)$, and $\widehat{cov}(\widehat{\theta}^c_j, \widehat{\rho}^c_j)$ are read from the estimated covariance matrix of the AR(1) model. The terms $\widehat{var}_{aug}(\widehat{b}_{i,0})$ and $\widehat{var}_{aug}(\widehat{b}_{i,j})$ are the first two diagonal elements of the 3×3 estimated covariance matrix of the coefficients of the augmented regression, $\widehat{V}_{aug}(\widehat{b}_{i,0}, \widehat{b}_{i,j}, \widehat{\phi}_{i,j})$, while $\widehat{cov}_{aug}(\widehat{b}_{i,0}, \widehat{b}_{i,j})$ is the first row-second column off-diagonal term. Note that $\widehat{var}_{aug}(\widehat{b}_{i,j})$ is the single-predictor counterpart to the estimated variance shown in Equation (A10).

In the multi-predictor case ($J > 1$), we follow the approach outlined in Appendix B.2 to compute the J-vector of estimated slope coefficients, $\widehat{b}_i$, and their covariance matrix, $\widehat{V}\left(\widehat{b}_i\right)$. The estimates for $\widehat{var}(\widehat{b}_{i,0})$ and $\widehat{cov}(\widehat{b}_{i,0}, \widehat{b}_i)$ are slightly more complicated than those shown in Equation (A18) because the estimated intercept, $\widehat{b}_{i,0}$, is a function of the J-vector of intercept, $\widehat{\theta}^c$, i.e., $\widehat{b}_{i,0} = b_{i,0} + \phi_i'(\widehat{\theta}^c - \theta)$. However, the logic behind the approach remains unchanged.

Table I

Descriptive Statistics

Panel A shows, for each investment category, the number of funds and their relative importance in the population (in parentheses), as well as the fund cross-sectional median and the 25-75% quantiles (in brackets) of the annualized excess mean (over the riskfree rate) and standard deviation, the skewness, and the kurtosis. Panel B displays the monthly mean and standard deviation, as well as the first-order autocorrelation and correlation matrix of the four predictive variables used to forecast hedge fund returns. Panel C displays the annualized excess mean and standard deviation, as well as the correlation matrix of the Fung and Hsieh (2004) seven risk factors. All statistics are computed using monthly observations between January 1994 and December 2007.

Panel A Fund Excess Returns

	Number(%)	Mean(Ann.)	Std(Ann.)	Skewness	Kurtosis
All Funds	7,991(100)	5.2%[1.2,9.5]	10.2%[6.4,16.6]	-.03 [-.41,.33]	3.7 [2.9,5.0]
Long-Short	1,393(17.4)	7.1 [2.7,11.5]	12.9 [8.8,17.9]	.03 [-.24,.35]	3.6 [2.8,4.5]
Market Neutral	217(2.7)	2.6 [-0.8,6.6]	7.4 [5.1,9.5]	-.07 [-.37,.29]	3.6 [2.9,5.1]
Managed Futures	830(10.4)	3.2 [-1.3,8.6]	15.4 [9.6,21.2]	.25 [.00,.54]	3.4 [2.8,4.4]
Global Macro	237(3.0)	5.5 [1.5,9.1]	13.3 [8.8,18.1]	.21 [-.20,.53]	3.7 [3.1,4.8]
Emerging Markets	389(4.9)	8.8 [3.7,19.1]	17.4 [10.2,23.1]	-.08 [-.33,.20]	3.3 [2.7,4.4]
Convertible Arb.	201(2.5)	3.3 [0.3,6.2]	5.5 [3.8,8.5]	-.23 [-.66,.13]	4.2 [3.4,5.8]
Event-Driven	277(3.5)	6.2 [2.8,10.7]	7.6 [5.1,11.7]	-.23 [-.71,.26]	4.6 [3.5,6.6]
Fixed Income	256(3.2)	3.0 [-0.3,5.7]	7.2 [3.9,9.6]	-.37 [-1.21,.12]	5.0 [3.4,8.2]
Funds of Funds	2,034(24.5)	3.9 [0.5,6.3]	7.0 [4.3,9.2]	-.31 [-.65,.06]	3.9 [3.1,5.3]
Multi-Strategy	687(8.6)	5.9 [2.2,10.6]	13.8 [8.2,22.2]	.16 [-.12,.46]	3.3 [2.6,4.6]

Panel B Predictors

				Correlation matrix		
	Mean(Mon.)	Std(Mon.)	Autocorr.	Dividend	VIX	Agg. Flows
Default Spread	0.8%	0.2%	0.95	-.26	.30	.19
Dividend Yield	2.0	0.4	0.97		-.48	-.26
VIX (Volatility)	19.5	6.7	0.84			.01
Aggregate Flows	0.9	2.0	0.23			

Panel C Risk Factor Returns

					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

Return and Alpha Predictability (In-Sample)

We measure hedge fund return and alpha predictability in the entire population, and across investment categories. In the first row (Return), we report, for each predictor (default spread, dividend yield, VIX, and aggregate flows), the estimated proportions of funds in the population exhibiting return predictability, $\widehat{\pi}_R^-$ and $\widehat{\pi}_R^+$ (- +). We also report the cross-fund median, $\overline{b}_j$, and 25-75% quantiles (in brackets) of the (bias-corrected) estimated slope coefficient shown in Equation (1). Each fund coefficient is standardized (by multiplying the initial estimate by the predictor standard deviation) so that it corresponds to the change in the fund monthly return for a one standard deviation increase in the predictor value. The final column (Joint) shows the estimated proportion of predictable funds using all predictors simultaneously, $\widehat{\pi}_R^{Joint}$. The inputs used to compute $\widehat{\pi}_R^{Joint}$ are the Wald tests of joint significance computed for each fund in the population. In the second row (Alpha), we repeat the same procedure using the (bias-corrected) estimated slope coefficients in Equation (2) to measure alpha predictability. All statistics are computed using monthly data between January 1994 and December 2007.

	Default Spread			Dividend Yield			VIX(Volatility)			Aggregate Flows			Joint
	−	+	Slope Coeff.	−	+	Slope Coeff.	−	+	Slope Coeff.	−	+	Slope Coeff.	
							All Funds						
Return	2.8	13.4	.07[-.21,.34]	22.2	4.1	-.11[-.43,.21]	22.7	3.1	-.14[-.50,.20]	33.2	0.0	-.23[-.56,.00]	60.5
Alpha	7.5	16.7	.04[-.22,.32]	21.7	3.4	-.11[-.44,.19]	21.0	4.9	-.10[-.46,.23]	26.7	0.0	-.15[-.43,.06]	59.3
							Long-Short Equity						
Return	7.1	10.2	.03[-.35,.41]	23.3	3.5	-.13[-.55,.28]	19.2	0.0	-.20[-.66,.19]	30.8	0.0	-.39[-.76,-.05]	58.7
Alpha	9.1	11.8	.03[-.35,.36]	28.2	1.6	-.22[-.65,.15]	24.0	4.8	-.15[-.61,.24]	25.5	0.0	-.18[-.52,.10]	58.9
							Market Neutral						
Return	12.2	4.0	.03[-.35,.41]	15.7	0.0	-.11[-.32,.10]	24.2	6.7	-.10[-.37,.15]	18.6	0.3	-.04[-.28,.15]	53.1
Alpha	22.3	11.5	.03[-.35,.36]	14.2	4.3	-.01[-.33,.18]	20.4	13.2	-.09[-.34,.20]	18.9	11.9	-.04[-.27,.19]	57.4
							Managed Futures						
Return	6.8	6.8	-.02[-.34,.36]	5.8	13.7	.04[-.40,.50]	0.0	16.7	.16[-.21,.62]	1.5	0.0	-.00[-.33,.30]	31.1
Alpha	10.2	9.6	-.02[-.36,.37]	5.1	14.7	.11[-.32,.55]	1.2	13.1	.14[-.25,.54]	6.8	0.0	-.06[-.38,.25]	34.1
							Global Macro						
Return	0.0	13.2	.06[-.27,.42]	19.8	4.2	-.14[-.69,.23]	14.5	10.2	.02[-.55,.36]	28.3	0.0	-.19[-.54,.18]	46.2
Alpha	4.7	17.3	.08[-.25,.44]	19.8	0.0	-.12[-.68,.21]	15.8	9.0	-.08[-.62,.27]	21.7	5.2	-.07[-.42,-.24]	42.5

Table II

Return and Alpha Predictability (Continued)

.

	Default Spread			Dividend Yield			VIX(Volatility)			Aggregate Flows			Joint
	−	+	Slope Coeff.	−	+	Slope Coeff.	−	+	Slope Coeff.	−	+	Slope Coeff.	
						Emerging Market							
Return	0.0	33.5	.43[-.03,1.14]	14.8	2.5	-.07[-.63,.30]	27.3	0.0	-.37[-1.08,.07]	37.9	0.0	-.54[-1.05,.16]	70.3
Alpha	0.0	37.9	.40[-.03,1.04]	20.9	2.4	-.19[-.70,.24]	37.9	3.0	-.45[-1.18,.07]	25.9	0.0	-.27[-.71,.04]	65.7
						Convertible Arbitrage							
Return	5.0	32.3	.12[-.07,.39]	32.6	2.7	-.11[-.34,.06]	24.9	17.9	-.06[-.39,.21]	44.7	0.0	-.17[-.46,-.05]	83.7
Alpha	9.0	28.0	.06[-.13,.34]	30.9	9.4	-.08[-.35,.14]	22.2	20.2	-.01[-.41,.30]	39.3	0.0	-.15[-.30,.01]	82.6
						Event-Driven							
Return	8.8	16.6	.05[-.20,.27]	37.8	2.6	-.12[-.46,.08]	39.0	0.0	-.26[-.62,.01]	34.4	0.0	-.19[-.42,-.03]	71.1
Alpha	18.0	8.3	-.03[-.27,.17]	28.5	0.0	-.11[-.43,.07]	30.8	1.0	-.14[-.47,.05]	22.2	0.0	-.09[-.34,.07]	56.1
						Fixed Income							
Return	10.2	20.7	.04[-.25,.26]	31.1	9.0	-.07[-.35,.12]	30.8	13.1	-.08[-.55,.20]	25.0	0.0	-.09[-.32,.04]	62.9
Alpha	18.0	19.5	.02[-.24,.20]	17.2	10.2	-.04[-.31,.17]	23.1	18.6	-.02[-.37,.29]	17.9	4.7	-.04[-.32,.09]	63.3
						Funds of Funds							
Return	0.0	15.1	.10[-.09,.26]	28.7	0.0	-.16[-.37,.04]	36.4	0.0	-.23[-.44,-.04]	65.1	0.0	-.29[-.52,-.14]	83.6
Alpha	3.0	19.7	.06[-.12,.22]	27.6	0.0	-.12[-.35,.06]	29.9	0.0	-.17[-.40,.00]	46.9	0.0	-.19[-.41,-.06]	79.2
						Multi-Strategy							
Return	1.6	9.9	.07[-.24,.42]	21.1	11.9	-.06[-.39,.42]	3.4	13.7	.11[-.26,.51]	7.5	0.0	-.10[-.38,.15]	40.5
Alpha	4.3	14.1	.07[-.26,.41]	11.5	9.6	-.03[-.40,.38]	3.8	7.9	.08[-.28,.46]	19.0	0.0	-.13[-.44,.10]	44.3

Table III

The Economic Value of Predictability (Out-of-Sample)

We compare the performance of the unconditional strategy with the one produced by different conditional strategies. The unconditional strategy selects funds with the highest unconditional t-statistic, while the conditional strategies (single-, multi-predictor, and combination) selects funds with the highest conditional t-statistic. While the single-predictor strategies use one of the four predictors (default spread, dividend yield, VIX, and aggregate flows) to forecast returns, the multi-predictor strategy uses all predictors simultaneously. Finally, the combination strategy averages across the single-predictor conditional t-statistics. 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, 2006. For comparison purposes, we also report the performance of hedge fund value-weighted (VW) and equally-weighted (EW) indices. In Panel A, we report the (annualized) Fung-Hsieh alpha, $\widehat{\alpha}$, residual standard deviation, $\widehat{\sigma}_{res}$, and Information Ratio, IR, the (annualized) excess mean, $\widehat{\mu}$, standard deviation, $\widehat{\sigma}_{tot}$, and Sharpe Ratio, SR, as well as the 1%- and 5%-Value-at-Risk, VaR. In Panel B, we compute the median and the 25-75% quantiles for the number of funds chosen each year, as well as the annual turnover. We also display the estimated first- and second-lag Fung-Hsieh residual autocorrelation and the average weights associated with the three investment categories in which the strategies invest most (LS, MF, and ED denote Long-Short, Managed Futures, and Event Driven, respectively). Panel C reports the portfolio sensitivity to the Fung-Hsieh risk factors along with the model explanatory power, R^2. Figures in parentheses denote the bootstrap p-values under the null hypothesis that the parameter is equal or inferior to the one associated with the unconditional strategy (one-sided test).

Panel A Out-of-Sample Performance (Jan. 1997-Dec. 2007)

	Fung-Hsieh Alpha (Ann.)			Excess Return (Ann.)			VaR	
	$\widehat{\alpha}$	$\widehat{\sigma}_{res}$	IR=$\widehat{\alpha}/\widehat{\sigma}_{res}$	$\widehat{\mu}$	$\widehat{\sigma}_{tot}$	SR=$\widehat{\mu}/\widehat{\sigma}_{tot}$	1%	5%
Unconditional	5.8%	2.4%	2.4	7.3%	4.2%	1.8	-1.5%	-0.9%
Single-Predic.								
Default Spread	7.8(.06)	3.9	2.0(.89)	9.2(.07)	5.7	1.6(.81)	-2.8	-1.0
Dividend Yield	6.5(.17)	3.5	1.8(.98)	8.5(.05)	5.7	1.5(.92)	-1.9	-1.2
VIX (Volatility)	6.2(.29)	3.5	1.8(.97)	7.8(.16)	5.0	1.5(.77)	-3.6	-1.5
Aggregate Flows	5.6(.62)	2.8	2.0(.91)	7.3(.49)	4.5	1.6(.82)	-2.6	-1.0
Multi-Predic.	5.3(.69)	3.4	1.5(.98)	6.6(.73)	4.6	1.4(.90)	-2.9	-1.3
Combination	7.0(.00)	2.6	2.7(.03)	8.5(.00)	4.5	1.9(.05)	-1.4	-0.7
Index (VW)	3.7(.96)	3.8	1.0(1.0)	5.5(.98)	5.3	1.0(1.0)	-2.6	-2.1
Index (EW)	4.1(.95)	3.1	1.3(1.0)	5.6(.98)	5.4	1.0(1.0)	-2.6	-2.0

Table III

The Economic Value of Predictability (Continued)

Panel B Portfolio Characteristics

	Nb. funds	Turn. (Ann)	Residual Autocorr. lag 1	Residual Autocorr. lag 2	Investment Categories LS	Investment Categories MF	Investment Categories ED
Unconditional	69[63,71]	59%[51,66]	.14	-.05	13.1%	6.2%	5.7%
Single-Predic.							
Default Spread	68[61,71]	80[70,85]	.22(.04)	.03(.13)	13.7	7.2	6.3
Dividend Yield	68[64,72]	76[61,77]	.21(.04)	.02(.09)	14.5	5.7	6.7
VIX (Volatility)	69[62,71]	68[64,78]	.03(.99)	.00(.06)	15.0	7.7	5.9
Aggregate Flows	70[61,72]	71[59,75]	.24(.01)	-.04(.79)	12.3	7.0	7.0
Multi-Predic.	68[59,72]	86[84,92]	.10(.78)	.00(.06)	11.9	10.5	6.3
Combination	69[62,71]	66[58,71]	.18(.13)	-.04(.52)	11.8	6.2	7.2
Index (VW)	808[606,947]	27[25,29]	.04(.97)	-.06(.37)	15.2	10.3	5.9
Index (EW)	808[606,947]	30[28,32]	.06(.92)	-.04(.27)	20.7	12.0	5.2

Panel C Sensitivity to the Fung-Hsieh Risk Factors

	Market	Size	Term	Default	T.Bond	T.Cur.	T.Com.	R^2
Unconditional	.15	.08	.10	.07	-.02	.00	.01	50.6%
Single-Predic.								
Default Spread	.19(.03)	.11(.07)	.08(.73)	.10(.40)	-.01(.11)	.00(.76)	.00(.90)	38.0
Dividend Yield	.20(.00)	.14(.00)	.18(.01)	.11(.24)	-.02(.74)	.01(.35)	.01(.38)	49.9
VIX (Volatility)	.14(.46)	.06(.93)	.11(.43)	.18(.03)	-.01(.27)	.01(.17)	.02(.00)	34.0
Aggregate Flows	.14(.68)	.07(.77)	.09(.65)	.25(.00)	-.01(.23)	.01(.42)	.00(.68)	47.8
Multi-Predic.								
	.09(.99)	.09(.36)	.09(.56)	.23(.02)	-.01(.10)	.01(.26)	.01(.36)	28.0
Combination	.14(.26)	.09(.13)	.10(.62)	.12(.04)	-.01(.38)	.00(.65)	.00(.81)	51.6
Index (VW)	.17(.07)	.10(.19)	.16(.10)	.25(.01)	.00(.00)	.01(.03)	.02(.02)	41.2
Index (EW)	.22(.00)	.15(.00)	.12(.25)	.17(.05)	.01(.00)	.02(.00)	.02(.04)	60.8

Table IV

Predictor Value and Performance
Single-Predictor Strategies

For each predictor (default spread, dividend yield, VIX, and aggregate flows), we sort its values observed on the 11 portfolio formation dates (from December 31, 1996 to December 31, 2006) into quintiles, and focus on the bottom and top quintiles. In Panel A, we report the characteristics (observed on the formation date) of each single-predictor strategy for the two quintiles (bottom and top). We compute the predictor value, $z_{j,t}$, the proportion of funds that are common to those held in the unconditional and slope portfolios (these are denoted by $\%_{uncond.}$ and $\%_{slope}$, respectively), and the average slope t-statistic, $t(\widehat{b}_j)$, across the funds selected by the strategy. Each value, $z_{j,t}$, is standardized, i.e., a value of one means that $z_{j,t}$ is one standard deviation higher than its normal level. The estimated slope coefficient of each fund is multiplied by $sign(z_{j,t})$ to guarantee that it is positive only when the fund has the right exposure to the predictor (i.e., when $sign(\widehat{b}_{i,j}) = sign(z_{j,t})$). In Panel B, we report the subsequent annual performance of each strategy following the formation date for the two quintiles (bottom and top). We report the (annualized) Fung-Hsieh alpha, $\widehat{\alpha}$, and Information Ratio, IR, as well as the (annualized) excess mean, $\widehat{\mu}$, and Sharpe Ratio, SR.

Panel A Portfolio Characteristics (Formation Dates)

	Bottom Quintile				Top Quintile			
	$z_{j,t}$	$\%_{uncond.}$	$\%_{slope}$	$t(\widehat{b}_j)$	$z_{j,t}$	$\%_{uncond.}$	$\%_{slope}$	$t(\widehat{b}_j)$
Default Spread	-1.65	58.1%	43.4%	0.96	4.81	28.2%	77.2%	2.03
Dividend Yield	-1.77	40.7	57.3	2.44	1.62	52.7	32.7	0.72
VIX (Volatility)	-1.16	51.3	46.0	1.84	2.04	44.0	56.7	1.04
Aggregate Flows	-1.26	64.0	27.3	0.87	1.29	56.9	37.6	0.36

Panel B Out-of-Sample Performance

	Bottom Quintile				Top Quintile			
	$\widehat{\alpha}$	IR	$\widehat{\mu}$	SR	$\widehat{\alpha}$	IR	$\widehat{\mu}$	SR
Default Spread	6.0%	1.9	7.5%	2.4	14.8%	2.2	14.4%	2.1
Dividend Yield	9.6	2.0	12.9	2.7	5.0	1.3	8.7	2.4
VIX (Volatility)	6.9	2.6	10.1	3.9	1.1	0.2	5.2	1.0
Aggregate Flows	5.6	1.5	6.7	1.8	2.3	1.1	7.6	3.4

Table V

Predictor Value and Performance Combination Strategy

For each predictor (default spread, dividend yield, VIX, and aggregate flows), we sort its values observed on the 11 portfolio formation dates (from December end 1996 to December end 2006) into quintiles, and focus on the bottom and top quintiles. For each predictor and each quintile (bottom and top), Panel A displays the characteristics (observed on the formation date) and the performance (measured over the subsequent year) of the combination long portfolio that only invests in funds that are included in the combination strategy but not in the unconditional strategy. We compute the predictor value, $z_{j,t}$, and the proportion of funds in the long portfolio that are common to those held by the slope portfolio, $\%_{slope}$. Each value, $z_{j,t}$, is standardized, i.e., a value of one means that the predictor value is one standard deviation higher than its normal level. We also report the difference in Fung-Hsieh alpha and mean between the long portfolio and the unconditional strategy, denoted by $\widehat{\alpha}$-$\widehat{\alpha}_u$ and $\widehat{\mu}$-$\widehat{\mu}_u$, respectively. Panel B repeats this analysis for the combination short portfolio that only invests in funds that are included in the unconditional strategy but not in the combination strategy.

Panel A Long Portfolio

	Bottom Quintile				Top Quintile			
	$z_{j,t}$	$\%_{slope}$	$\widehat{\alpha}-\widehat{\alpha}_u$	$\widehat{\mu}-\widehat{\mu}_u$	$z_{j,t}$	$\%_{slope}$	$\widehat{\alpha}-\widehat{\alpha}_u$	$\widehat{\mu}-\widehat{\mu}_u$
Default Spread	-1.65	8.1%	5.3%	5.2%	4.81	10.1%	4.7%	4.6%
Dividend Yield	-1.77	11.2	3.2	3.7	1.62	6.0	1.9	3.5
VIX (Volatility)	-1.16	14.0	2.4	4.7	2.04	9.1	3.2	3.7
Aggregate Flows	-1.26	2.0	1.5	2.2	1.29	8.3	0.0	3.1

Panel B Short Portfolio

	Bottom Quintile				Top Quintile			
	$z_{j,t}$	$\%_{slope}$	$\widehat{\alpha}-\widehat{\alpha}_u$	$\widehat{\mu}-\widehat{\mu}_u$	$z_{j,t}$	$\%_{slope}$	$\widehat{\alpha}-\widehat{\alpha}_u$	$\widehat{\mu}-\widehat{\mu}_u$
Default Spread	-1.65	0.0%	-5.5%	-3.7%	4.81	0.0%	-2.7%	-3.7%
Dividend Yield	-1.77	0.0	-2.0	0.3	1.62	0.0	0.0	-1.3
VIX (Volatility)	-1.16	0.0	-1.5	-1.1	2.04	0.0	-2.0	0.3
Aggregate Flows	-1.26	0.0	-0.5	-1.9	1.29	0.0	2.2	2.9

Table VI

The 2008 Financial Crisis

In Panel A, we compare the performance of the unconditional strategy with the one obtained by different conditional strategies (single-, multi-predictor, and combination) after including the 2008 financial crisis. We report the (annualized) Fung-Hsieh alpha, $\widehat{\alpha}$, residual standard deviation, $\widehat{\sigma}_{res}$, and Information Ratio, IR, the (annualized) excess mean, $\widehat{\mu}$, standard deviation, $\widehat{\sigma}_{tot}$, and Sharpe Ratio, SR, as well as the 2008 cumulative returns during the periods January-September and October-December. Figures in parentheses denote the bootstrap p-values under the null hypothesis that the parameter is equal or inferior to the one associated with the unconditional strategy (one-sided test). In Panel B, we examine, for each single-predictor strategy, the stability of the estimated slope coefficient in 2008. We first report the predictor value, z_j, as well as the proportion of funds that are common to those held in the unconditional and slope portfolios, $\%_{uncond.}$ and $\%_{slope}$, on the final formation date in December 31, 2007. Each value, z_j, is standardized, i.e., a value of one means that z_j is one standard deviation higher than its normal level. Then, we compute two hit ratios that determine the proportion of months in 2008 when: 1) the estimated portfolio predictable component is positive ($\widehat{b}_{j,t} z_{j,t} > 0$); 2) the predictor value has the same sign as the one observed on December 31, 2007 ($z_j z_{j,t} > 0$). For comparative purposes, we report the same statistics computed during previous years (excluding 2008) following an extreme predictor value (we use the values included in either the bottom or top quintile in Table IV, depending on the sign of z_j). In Panel C, we measure the performance of the unconditional and unconditional strategies between January 1997 and December 2008, assuming that the investor can rebalance his portfolio at a monthly frequency in 2008. The Δ reports the difference in performance with the baseline strategies in Panel A.

Panel A Out-of-Sample Performance (Jan. 1997-Dec. 2008)

	Fung-Hsieh Alpha (Ann.)			Excess Return (Ann.)			Cum. Return 2008	
	$\widehat{\alpha}$	$\widehat{\sigma}_{res}$	IR	$\widehat{\mu}$	$\widehat{\sigma}_{tot}$	SR	Jan-Sep	Oct-Dec
Unconditional	4.1%	3.4%	1.2	4.9%	5.1%	0.9	-5.4%	-14.1%
Single-Predictor								
Default Spread	6.2(.02)	4.2	1.5(.11)	6.8(.03)	6.3	1.1(.14)	-4.9	-12.3
Dividend Yield	5.8(.03)	3.8	1.5(.07)	7.0(.00)	5.9	1.2(.07)	0.1	-8.6
VIX (Volatility)	6.3(.01)	3.8	1.7(.08)	7.2(.01)	5.1	1.4(.02)	4.7	-3.1
Aggregate Flows	4.2(.41)	3.4	1.2(.44)	4.9(.49)	5.3	0.9(.60)	-5.1	-14.1
Multi-Predictor	4.9(.22)	3.6	1.3(.32)	5.6(.26)	4.7	1.2(.14)	0.7	-4.7
Combination	6.0(.00)	3.1	1.9(.00)	6.7(.00)	5.1	1.3(.00)	0.2	-11.2

Table VI

Impact of the 2008 Financial Crisis (Continued)

Panel B Stability of the Slope Coefficients

	December 07 (Formation date)			Jan.-Dec. 2008 Hit Ratios (> 0)		Jan. 1997-Dec. 2007 Hit Ratios (> 0)	
	z_j	$\%_{uncond.}$	$\%_{slope}$	$\widehat{b}_{j,t} \cdot z_{j,t}$	$z_j \cdot z_{j,t}$	$\widehat{b}_{j,t} \cdot z_{j,t}$	$z_j \cdot z_{j,t}$
Single-Predictor							
Default Spread	3.17	24.0%	62.7%	25.0%	100%	87.5%	100%
Dividend Yield	3.36	21.3	73.3	16.6	100	83.3	100
Volatility (VIX)	2.46	24.0	76.0	83.3	100	70.8	95.8
Aggregate Flows	-1.33	54.7	48.0	50.0	75.0	70.8	66.6

Panel C Cost of Liquidity Constraints

	Fung-Hsieh Alpha (Ann.)				Excess Return (Ann.)				Cum. Return 2008	
	$\widehat{\alpha}$	Δ	IR	Δ	$\widehat{\mu}$	Δ	SR	Δ	Jan-Sep	Oct-Dec
Unconditional	5.6%	1.5	1.8	0.6(.00)	6.4%	1.5	1.5	0.6(.01)	-1.6%	-0.6%
Single-Predictor										
Default Spread	8.2	2.0	1.6	0.1(.28)	8.6	1.8	1.4	0.3(.06)	-4.0	7.6
Dividend Yield	7.3	1.5	1.5	0.0(.56)	8.3	1.3	1.3	0.1(.17)	-2.6	9.7
VIX (Volatility)	6.9	0.6	1.6	-0.1(.71)	7.7	0.5	1.5	0.1(.30)	-2.0	6.1
Aggregate Flows	6.6	2.4	1.6	0.4(.06)	7.0	2.1	1.4	0.5(.01)	-0.7	5.9
Multi-Predictor	4.7	-0.2	1.2	-0.1(.89)	5.4	0.2	1.1	-0.1(.79)	-1.6	-4.6
Combination	7.7	1.7	1.9	0.0(.51)	8.2	1.5	1.6	0.3(.06)	-0.5	7.4

Table VII
Sensitivity Analysis

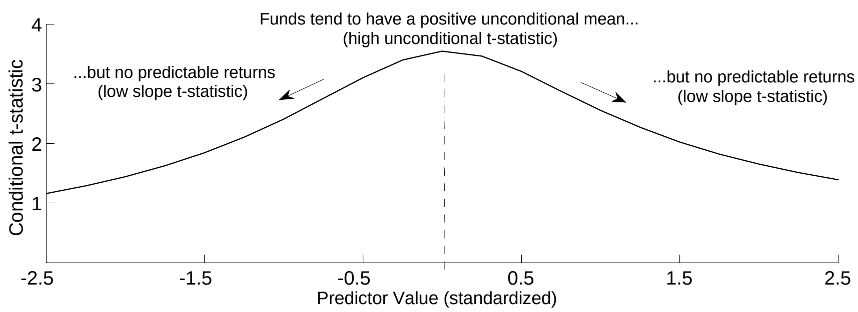
We examine whether performance is sensitive to changes in the baseline specification. We consider the following cases: the maximum number of funds in the portfolio is either equal to 50 or unlimited (baseline case: 75 funds); there is no AuM cutoff (baseline case: small funds are discarded); there is a -25% monthly return penalty when a fund has a missing observation (baseline case: 0% penalty); we assume that returns over the previous month are not available in the hedge fund databases (baseline case: 0 month); we impose a three-month notice period prior to withdrawal (baseline case: 0 months); we use the *t*-statistic of the fund conditional alphas to select funds (baseline case: conditional mean). In each case, we report the (annualized) Fung-Hsieh alpha, $\widehat{\alpha}$, Information Ratio, IR, excess mean, $\widehat{\mu}$, and Sharpe Ratio, SR, during the periods January 1997-December 2007 and January 1997-December 2008. Figures in parentheses denote the bootstrap *p*-values under the null hypothesis that the difference in IR (SR) between the combination and the unconditional strategies is zero or less (one-sided test).

		Jan. 1997-Dec. 2007				Jan. 1997-Dec. 2008			
		$\widehat{\alpha}$	IR	$\widehat{\mu}$	SR	$\widehat{\alpha}$	IR	$\widehat{\mu}$	SR
Portfolio Size:	Unconditional	5.9	2.7	7.1	1.9	4.5	1.6	5.2	1.2
50 Funds	Combination	7.3	3.0(.08)	8.6	2.0(.08)	6.3	2.2(.02)	6.9	1.5(.01)
Portfolio Size:	Unconditional	6.1	2.4	7.6	1.7	4.4	1.3	5.2	1.0
Unlimited	Combination	7.0	2.5(.14)	8.5	1.8(.08)	5.8	1.8(.00)	6.6	1.2(.00)
AUM Cutoff:	Unconditional	6.7	2.9	8.0	1.9	5.9	2.3	6.5	1.5
No Cutoff	Combination	7.5	3.2(.03)	9.0	2.0(.09)	6.7	2.6(.04)	7.4	1.6(.13)
Missing Return:	Unconditional	3.3	1.1	4.6	1.1	1.5	0.4	2.2	0.4
-25% Penalty	Combination	4.6	1.5(.01)	5.8	1.3(.01)	3.4	1.0(.00)	4.0	0.8(.00)
Data Availability:	Unconditional	5.4	2.1	6.9	1.6	3.7	1.1	4.5	0.9
1 Month Lag	Combination	6.3	2.4(.07)	8.0	1.7(.09)	5.2	1.6(.00)	6.0	1.1(.00)
Notice Period:	Unconditional	5.0	2.1	6.3	1.6	3.4	1.1	4.1	0.8
3 Months	Combination	5.4	2.2(.24)	6.3	1.8(.10)	4.4	1.6(.01)	4.8	1.2(.00)
Alpha	Unconditional	6.4	2.5	7.7	1.9	5.2	1.9	5.9	1.4
Predictability	Combination	7.7	2.9(.07)	8.9	2.0(.27)	6.7	2.2(.06)	7.1	1.5(.19)

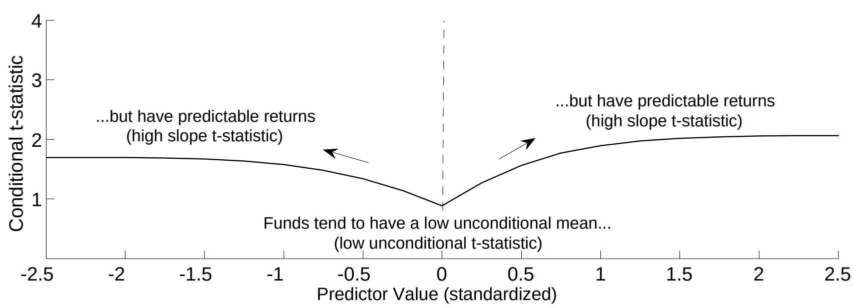
Figure 1

The Trade-off between Unconditional and Predictable Performance

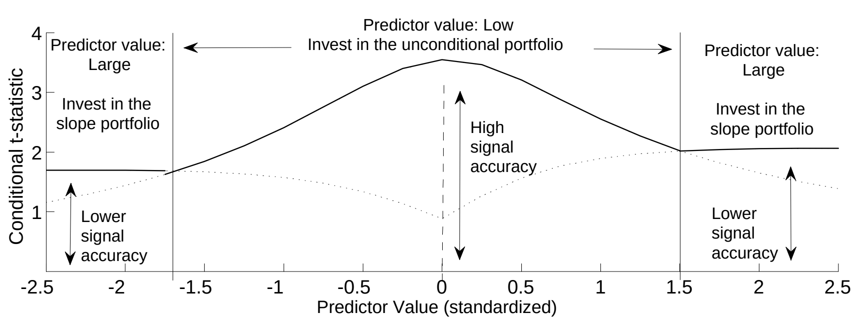
We plot the relation between the predictor value and the conditional t-statistic of the unconditional and slope portfolios in Plots A and B, respectively. The unconditional (slope) portfolio holds the top decile of funds with the highest unconditional (slope) t-statistic. Each graph is constructed from our hedge fund dataset (to be presented), using the default spread as a single predictor. For each fund i included in the unconditional (slope) portfolio in month t, we use past data to compute $t(\widehat{\mu}_i)$, $\widehat{var}(\widehat{\mu}_i)$, $t(\widehat{b}_{i,j})$, $\widehat{var}(\widehat{b}_{i,j})$, and $\widehat{var}(\widehat{\mu}_{i,t})$. Then, we average these estimates across funds and months, and plug these averages into Equation (7) to obtain the conditional t-statistic for each portfolio. In Plot C, we illustrate the investment process of the single-predictor strategy that holds the top decile of funds with the highest conditional t-statistic.



(A) Unconditional Portfolio



(B) Slope Portfolio

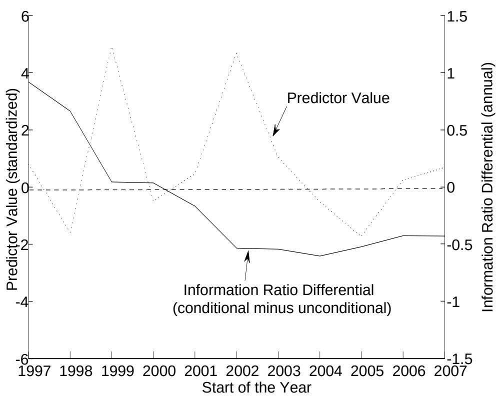


(C) Single-Predictor Strategy

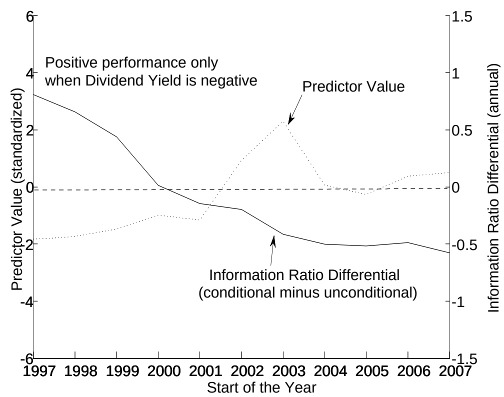
Figure 2

Variation in the Performance of the Single-Predictor Strategies

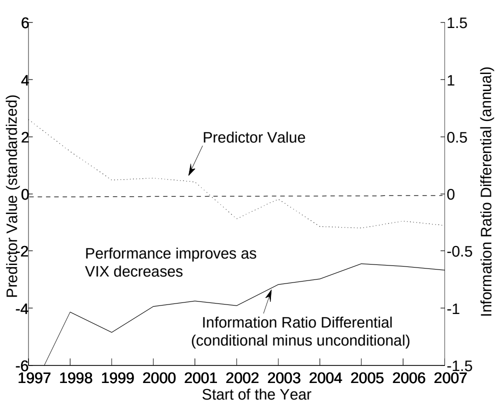
For each predictor, we examine the relation between its value during the portfolio formation date (December end) and the change in performance of the single-predictor strategy over the subsequent year. The results for the default spread, the dividend yield, the VIX, and aggregate flows are displayed in Plots A to D. The predictor value is standardized, i.e., a value of one means that its value is one standard deviation higher than its normal level. Performance is measured as the difference in Information Ratio between the single-predictor strategy and the unconditional portfolio, computed using an expanding window that includes the return data up to the end of the year. Specifically, the initial observation in 1997 corresponds to the predictor value observed in December 1996 along with the portfolio performance measured from January 1997 to December 1997. The final observation in 2007 corresponds to the predictor value in December 2006 along with the portfolio performance measured from January 1997 to December 2007.



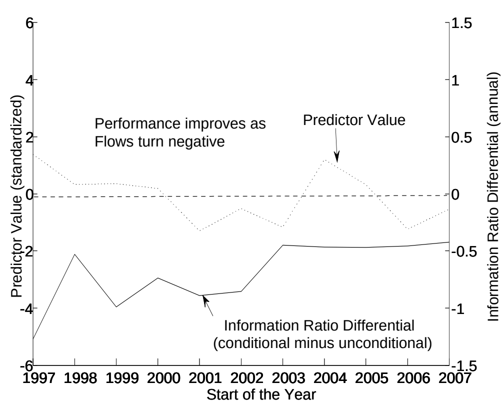
(A) Default Spread



(B) Dividend Yield



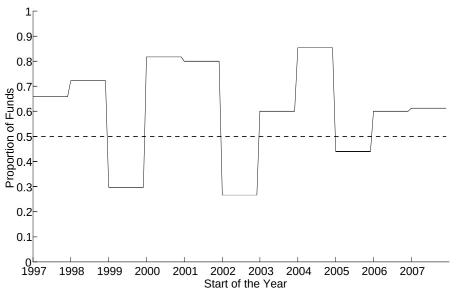
(C) VIX (Volatility)



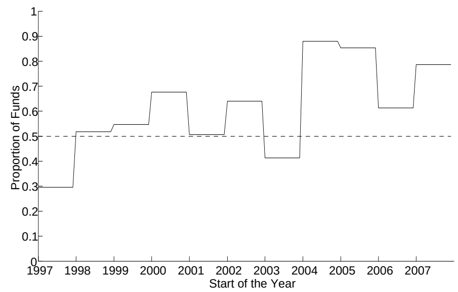
(D) Aggregate Flows

Figure 3
Commonality with the Unconditional Portfolio

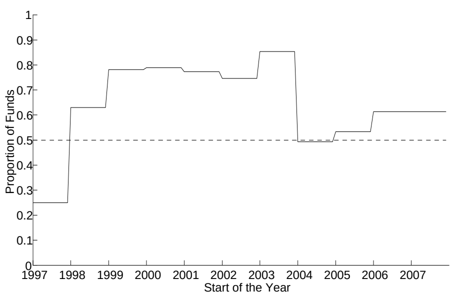
We show the evolution of the proportion of funds chosen by each conditional strategy that are common to those included in the unconditional portfolio between January 1997 and December 2007. Plots A to D show the results for the single-predictor strategies (default spread, dividend yield, VIX, and aggregate flows). Panels E and F display the results for the multi-predictor and the combination strategies, respectively.



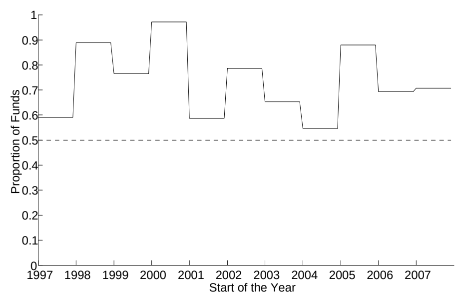
(A) Default Spread



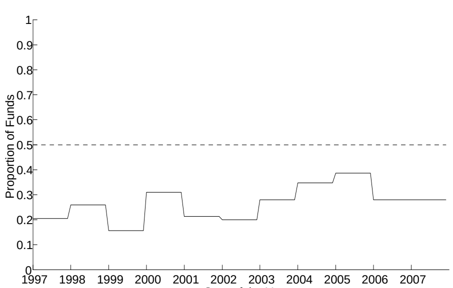
(B) Dividend Yield



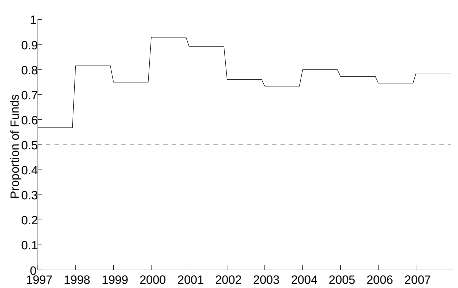
(C) VIX (Volatility)



(D) Aggregate Flows



(E) Multi-Predictor



(F) Combination Strategy