Appendix to "Hedge Fund Return Predictability under the Magnifying Glass"

I Estimation Procedure

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:

$$\begin{aligned} r_{i,t+1} &= b_{i,0} + b_i' Z_t + u_{i,t+1}, \\ Z_{t+1} &= C + \Phi Z_t + \upsilon_{t+1}, \end{aligned} \tag{A1}$$

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, C is a J-vector of constants, 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 υ_{t+1} the J-vector of predictor innovations between time t and $t+1$. We assume that $u_{i,t+1} = E\left(u_{i,t+1} \left| \upsilon_{t+1}\right.\right) + e_{i,t+1} = \phi_i' \upsilon_{t+1} + e_{i,t+1}$, 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 υ_{t+1}).

To construct a proxy, υ_{t+1}^c, for the unobserved J-vector υ_{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 $\widehat{C}$ and $\widehat{\Phi}$. Based on these estimates, we obtain the time-series of estimated innovation vector, $\widehat{\upsilon}_{t+1}$, from which we compute the $J \times J$ innovation covariance matrix, denoted by $\widehat{\Sigma}_{\upsilon}$. Second, we use $\widehat{C}$, $\widehat{\Phi}$, and $\widehat{\Sigma}_{\upsilon}$ to correct for the small-sample bias in $\widehat{\Phi}$ using the analytical formula proposed by Nicholls and Pope (1988):

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

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: $vec(\Sigma_\upsilon) = (I_{J^2} - A)vec(\Sigma_Z)$, 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 q ($q = 2, ..., Q$), we use the following updating scheme: $\widehat{\Phi}_{(q)} = \widehat{\Phi} - \widehat{bias}(\widehat{\Phi})_{(q)}$ and $\widehat{C}_{(q)} = \left(I - \widehat{\Phi}_{(q)}\right)\overline{Z}$, where $\overline{Z}$ denotes the sample mean, and $\widehat{\Sigma}_{\upsilon(q)}$ is obtained using the updated estimates, $\widehat{\Phi}_{(q)}$ and $\widehat{C}_{(q)}$. As in AHW, the number of iterations, Q, is set equal to 10. Third, we use the final bias-corrected VAR(1) estimates, $\widehat{C}^c$ and $\widehat{\Phi}^c$, to construct the proxy υ_t^c:

$$\upsilon_t^c = Z_{t+1} - \widehat{C}^c + \widehat{\Phi}^c Z_t. \qquad \text{(A3)}$$

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) of the paper, 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 $\upsilon_{t+1}^c + (\widehat{C}^c - C) + \left(\widehat{\Phi}^c - \Phi\right) Z_t$, we find that the remaining bias in the J-vector, $\widehat{b}_i$, is equal to $E\left(\widehat{\Phi}^c - \Phi\right)'\phi_i$. We see that $\widehat{b}_i$ is nearly unbiased since the bias-corrected companion matrix, $\widehat{\Phi}^c$, gets very close to the true value, Φ.[1]

[1]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 $bias(\widehat{\Phi}) = \widehat{bias}(\widehat{\Phi}) + O(T^{-\frac{3}{2}})$.

A.2 Alpha Predictability

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

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

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 $X_t = [1, Z_{t-1}', f_t', \omega_t']'$.

The small-sample bias in the J-vector of OLS-estimated alpha slope coefficients can be eliminated if we include the J-vector ω_{t+1} as an 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., $E\left(\varrho_i \left| X \right.\right) = 0$, where $\varrho_i = [\varrho_{i,1}, ..., \varrho_{i,T+1}]'$, $X = [X_1, ..., X_{T+1}]'$. 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 benchmark 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: $X_t = [1, Z_t', f_{t+1}', \omega_{t+1}^{c\prime}]'$. We can replace $\epsilon_{i,t+1}$ with $\psi_i'\omega_{t+1} + \varrho_{i,t+1}$ in Equation (A4), where

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

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

B Estimating the Variance of the Slope Coefficient

We show how to compute the variance of the estimated slope coefficients under illiquidity. For sake of brevity, we focus on return predictability, but the procedure is similar for alpha. AHW show that the estimated variance of the bias-corrected slope coefficient, $\widehat{b}_{i,j}$, associated with each predictor j $(j = 1, ..., J)$ can be written as

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

where $\widehat{\rho}_{k,j}^z$ denotes the k^{th} row-j^{th} column element of the estimated companion matrix, $\widehat{\Phi}^c$, and $\widehat{\phi}_{i,k}$ is the k^{th} element of the J-vector of estimated innovation coefficients, $\widehat{\phi}_i$. The terms $\widehat{cov}(\widehat{\rho}_{k,j}^z, \widehat{\rho}_{l,j}^z)$ 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, $\widehat{V}_{aug} = \widehat{V}_{aug}(\widehat{b}_{i,0}, \widehat{b}_i, \widehat{\phi}_i)$.

The expression for $\widehat{V}_{aug}$ is affected by return illiquidity. Specifically, if the fund reported residuals, $e_{i,t+1}^0$, are autocorrelated, $\widehat{V}_{aug}$ is equal to $(X'X)^{-1}\left(X'\widehat{V}_iX\right)(X'X)^{-1}$, where $X_{(T\times(2\cdot J+1))} = [X_1, ..., X_t, ..., X_{T+1}]'$, $X_t = [1, Z_t', \upsilon_{t+1}^{c\prime}]'$, and $\widehat{V}_i$ is the $T\times T$ estimated covariance matrix of the residual vector $e_i^0 = \left[e_{i,2}^0, ..., e_{i,T+1}^0\right]'$. If $e_{i,t+1}^0$ follows a $MA(2)$ process as in Getmansky, Lo, and Makarov (2004; GLM hereafter), i.e., $e_{i,t+1}^0 = \theta_{i,0}\eta_{i,t+1} + \theta_{i,1}\eta_{i,t} + \theta_{i,2}\eta_{i,t-1}$, we have

$$V_i = \widehat{var}(e^0_{i,t+1}) \begin{bmatrix} 1 & \widehat{\rho}_{i,1} & \widehat{\rho}_{i,2} & 0 & 0 & ... & 0 & 0 & 0 \\ \widehat{\rho}_{i,1} & 1 & \widehat{\rho}_{i,1} & \widehat{\rho}_{i,2} & 0 & ... & 0 & 0 & 0 \\ \widehat{\rho}_{i,2} & \widehat{\rho}_{i,1} & 1 & \widehat{\rho}_{i,1} & \widehat{\rho}_{i,2} & ... & 0 & 0 & 0 \\ ... & ... & ... & ... & ... & ... & ... & ... & ... \\ 0 & 0 & 0 & 0 & 0 & ... & \widehat{\rho}_{i,2} & \widehat{\rho}_{i,1} & 1 \end{bmatrix}, \tag{A12}$$

where $\widehat{\rho}_{i,1}$ and $\widehat{\rho}_{i,2}$ are the estimated first- and second-order autocorrelation coefficients. Sample estimates obtained from the estimated reported residuals, $\widehat{e}^0_{i,t+1}$, are consistent, but biased downward in small samples (e.g., Marriott and Pope (1954)).[2] We can easily correct for this bias using a bootstrap approach. First, in each iteration q ($q = 1, ..., 1,000$), we simulate the following system forward:

$$\begin{aligned} Z^q_{t+1} &= \Phi Z^q_t + \upsilon^q_{t+1}, \\ e^{0,q}_{t+1} &= \theta_0 \eta^q_{t+1} + \theta_1 \eta^q_t + \theta_2 \eta^q_{t-1}, \\ r^{0,q}_{t+1} &= b' Z^q_t + \phi' \upsilon^q_{t+1} + e^{0,q}_{t+1}, \qquad t = 2, ..., T+1, \end{aligned} \tag{A13}$$

where T is the number of return observations, Z_1 (the initial observation) is drawn from a normal $N(0, \Sigma_Z)$, υ_{t+1} from a normal $N(0, \Sigma_\upsilon)$, and η^q_{t+1}, η^q_t, η^q_{t-1} from a normal $N(0,\sigma^2_\eta)$ with $\sigma^2_\eta = var(e^0_{t+1})/(\theta^2_0 + \theta^2_1 + \theta^2_2)$. All parameters ($\Phi$, θ_0, θ_1, θ_2, b, ϕ, Σ_Z, Σ_υ, $var(e^0_{t+1})$) are computed from the original sample data. In particular, the elements of the J-vectors, b and ϕ, as well as $var(e^0_{t+1})$ are equal to the median across all funds. To determine θ_0, θ_1, θ_2 from the median autocorrelation coefficients, ρ_1 and ρ_2, obtained from the data, we simply match the following two moments:

$$\begin{aligned} \rho_1 &= (\theta_0\theta_1 + \theta_1\theta_2)/(\theta^2_0 + \theta^2_1 + \theta^2_2) \\ \rho_2 &= \theta_1\theta_2/(\theta^2_0 + \theta^2_1 + \theta^2_2), \end{aligned} \tag{A14}$$

[2]We find that the estimated bias of the sample first-order autocorrelation equals -0.08 for $T = 50$, and quickly vanishes as T increases (e.g., it amounts to -0.03 for $T = 100$).

subject to $\theta_0+\theta_1+\theta_2=1$ and the invertibility constraints, $\theta_1<1/2$, $\theta_1<1-2\theta_2$ (see GLM, proposition 3). We compute the estimated residuals, $\widehat{e}^{0,q}_{t+1}$, from the regression of $r^{0,q}_{t+1}$ on $X^q_t=[1,Z^{q\prime}_t,\upsilon^{q\prime}_{t+1}]'$, and use them to obtain the sample autocorrelations, $\widehat{\rho}^q_1$, and $\widehat{\rho}^q_2$. Second, after 1,000 iterations, we estimate the $\text{bias}_l(T)$ as $\sum_{q=1}^{1,000}(\widehat{\rho}^q_l-\rho_l)$ for $l=1,2$. Third, for a fund with T_i return observations, we compute $\widehat{\rho}_{i,1}$ and $\widehat{\rho}_{i,2}$ as the sample autocorrelations minus $\text{bias}_1(T_i)$ and $\text{bias}_2(T_i)$, respectively, and insert these values in Equation (A12).

C Estimating the Proportions of Funds with Predictable Returns

For each predictor j ($j=1,...,J$), we use the method proposed by Barras, Scaillet, and Wermers (2010) to estimate the proportions of funds with predictable returns, $\pi^-_R(j)$, and $\pi^+_R(j)$. 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. The proportions of funds with predictable alphas are computed along the same lines.

We also compute the estimated proportion of funds with predictable returns, $\widehat{\pi}^{Joint}_R$, using all predictors simultaneously (shown in the final column of Table I of the paper). 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

For each predictor j ($j = 1, ..., J$), the single-predictor strategy selects funds with the highest conditional t-statistic, $t(\widehat{\mu}_{i,t}(j)) = \widehat{\mu}_{i,t}(j)/\widehat{var}(\widehat{\mu}_{i,t}(j))^{\frac{1}{2}}$, where $\widehat{\mu}_{i,t}(j)$ is the fund estimated conditional mean and $\widehat{var}(\widehat{\mu}_{i,t}(j))$ denotes its estimated variance (see Equation (4) of the paper). To compute the conditional t-statistic, we can write $\widehat{\mu}_{i,t}(j)$ and $\widehat{var}(\widehat{\mu}_{i,t}(j))^{\frac{1}{2}}$ as

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

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 $j : Z_{j,t+1} = \widehat{c}_j + \widehat{\rho}_j^z Z_{j,t} + \widehat{\upsilon}_{j,t+1}$. Second, we replace the unobservable innovation term, $\upsilon_{j,t+1}$, with $\upsilon_{j,t+1}^c = Z_{j,t+1} - \widehat{c}_j^c - \widehat{\rho}_j^{z,c} Z_{j,t}$, where $\widehat{c}_j^c$ and $\widehat{\rho}_j^{z,c}$ are the second-order bias corrected coefficients suggested by AH:

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

where T denotes the number of return observations, and $\overline{Z}_j$ denotes the sample mean. Third, we regress the hedge fund return on the augmented vector X_t including 3 explanatory variables, $X_t = [1, Z_{j,t}, \upsilon_{j,t+1}^c]'$. 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 $\widehat{b}_{i,j}$, and their covariance as

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

where $\widehat{var}(\widehat{c}_j^c)$, $\widehat{var}(\widehat{\rho}_j^{z,c})$, and $\widehat{cov}(\widehat{c}_j^c, \widehat{\rho}_j^{z,c})$ 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 $\widehat{var}(\widehat{b}_{i,j})$ is the single-predictor counterpart to the estimated variance shown in Equation (A10).

II Data Description

We evaluate hedge fund performance using monthly net-of-fee returns of live and dead hedge funds using a new database that aggregates data reported in BarclayHedge, TASS, HFR, CISDM and MSCI. The union of these databases represents, to our knowledge, the largest data set of hedge funds to date. 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.[3] In addition, we start our analysis in 1994 because prior to that date, databases did not keep track of the hedge funds that died. Finally, funds often report return data prior to their listing date in the database, thereby creating a backfill bias. Since well-performing funds have strong incentives to list, the backfilled returns are usually higher than the non-backfilled returns. To address this issue, we exclude the first 12 months of data for each fund. To allow a detailed interpretation of predictability results per strategy, we choose to group funds into 10 different investment styles.

To select the hedge fund risk factors, we use the Fung-Hsieh seven-factor model (2004). The two equity factors are the S&P 500 return minus the risk freerate (equity market), and the Wilshire small cap minus large cap returns (equity size), respectively. To replace the

[3] 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 and correlations, as well as their differences in AuM. When multiple shareclasses are identified, we use the oldest US dollar shareclass.

non-tradable Fung-Hsieh bond factors, we use two bond indices constructed by Barclays Capital (available on Datastream). Specifically, the term factor (bond term) is proxied by the total return of the Barclays Capital US Treasury long-term government bond index (7-10 year) minus the riskfree rate. The default factor (bond default) is proxied by the total return of the Barclays Capital corporate bond index (BAA) minus the risk freerate.[4] Finally, we denote by trend bond, trend currency, and trend commodity, the excess return of the straddle-type trend following strategies.

In Table AI, we report descriptive statistics for the hedge funds population, the four predictive variables, and the seven tradable Fung-Hsieh risk factors, respectively. The sample period ranges from January 1994 to December 2008. Compared to previous studies, the hedge fund average returns reported in Panel A are lower, reflecting the large losses incurred by many funds during the recent financial crisis. Turning to Panel B, we observe that the default spread, the dividend yield, and the VIX exhibit high positive autocorrelation. These large coefficients highlight the importance of controlling for small sample bias in the estimation process.[5] 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 implemented in the paper could add value over individual predictors.

Please insert Table AI here

[4]Note that the factor "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).

[5]Including 2008 leads to a large increase in the estimated autocorrelation coefficients because of the extreme, but temporary, deviations of the predictors from their past historical average. For instance, between December 2007 and December 2008, the default spread and the dividend yield have increased by 250% and 76%, respectively.

III Additional Empirical Results

A Fund Illiquidity Profiles

Table AII shows the fund illiquidity profiles for all funds in the population, as well as for the different investment categories over the period January 1994-December 2008. The first row (Return) contains the estimated proportions of funds having reported returns, $r^0_{i,t+1}$, that are negatively and positively autocorrelated at the first two lags. The third row-element (Test MA(2)) displays the proportion of funds for which the MA(2) specification is rejected. All these proportions are computed using the approach in Barras, Scaillet, and Wermers (2010) described above. Similar to Table 8 in Getmansky, Lo, and Makarov (2004; GLM hereafter), we also report the cross-sectional mean and standard deviation of the MA(2) parameters, $\widehat{\theta}_{i,0}$, $\widehat{\theta}_{i,1}$ and $\widehat{\theta}_{i,2}$, obtained from the moment matching technique shown in Equation (A14). The second row (Residual) reports the same information using the fund reported residuals, $e^0_{i,t+1}$.

Please insert Table AII here

First, the MA(2) specification does a very good job at capturing serial correlation in the data. The model is rejected for only 3.2% and 0.2% of the funds when fitted on returns and residuals, respectively. Second, we find that a large fraction of the funds have positively autocorrelated returns at the first two lags (50.1% and 21.5% of funds, respectively). To estimate the degree of autocorrelation that is purely driven by illiquidity, we examine the results obtained with the fund reported residuals. The estimated proportions at the first two lags are far lower than their return counterparts (23.3% and 6.9%, respectively), but still comfortably above zero. It implies that time-variation in expected returns is an important driver of serial correlation, although it cannot alone explain the level observed in the data. Finally, we find that the fund illiquidity profiles captured by the MA(2) coefficients are very similar to those reported in GLM. In particular, the variation across investment categories is consistent with their exposures to illiquidity. For instance, $\widehat{\theta}_{i,0}$, which reveals the speed at which new information is reflected into reported returns, is lower on average for emerging market or convertible arbitrage funds, and higher for managed futures funds.

B In-Sample Analysis

B.1 Hedge fund Leverage

To further examine whether changes in fund leverage impact future returns (alphas), we replace the dividend yield in the predictive regression with two measures of leverage availability/cost. The first one is the past annual return of a Prime Broker Index (PBI) that includes Bank of America, Bank of New York Mellon, Bear Stearns, Citigroup, Credit Suisse, Deutsche Bank, Goldman Sachs, Lehman Brothers, Morgan Stanley, Merrill Lynch, and UBS (see Boyson, Stahel, and Stulz (2010)). The second variable is the TED spread, defined as the difference between the 3-month Eurodollar deposit rate and the 3-month Treasury Bill.

If prime brokers have suffered from important losses over the recent past, they may be more reluctant to provide leverage, thus reducing future hedge fund performance. If this is the case, we expect the slope coefficient associated with PBI to be positive. The results shown in Table AIII (Specification 1) confirm this intuition. In the entire population (all funds), the proportion of funds having returns (alphas) that are positively related to PBI, $\widehat{\pi}_R^+$ ($\widehat{\pi}_\alpha^+$), amounts to 26.7% (32%), while $\widehat{\pi}_R^-$ ($\widehat{\pi}_\alpha^-$) equals zero. Importantly, the results mirror those obtained with the dividend yield very closely. First, the estimated proportions of funds with predictable returns (alphas), along with the slope coefficients have similar magnitudes, both in the entire population and across investment categories. Second, managed futures is the only category for which the evidence of predictability is very weak.

As discussed in Ang, Gorovyy, and van Inwegen (2011), prime brokers tend to pass any increase in the TED spread to their clients. As a result, we expect a higher-than-average TED spread to be associated with lower future returns (alphas), as hedge fund leverage becomes more expensive. The results in Table AIII (Specification 2) show that this is indeed the case.

Please insert Table AIII here

A small subset of funds in our database (5,112 funds from TASS and BarclayHedge) report a static measure of their average leverage levels. As a final check, we measure the predictive ability of the dividend yield on the future returns of funds that do not use leverage on average and those using it. Consistent with our leverage-based explanation, we find that the proportion of funds with a negative exposure to the dividend yield is higher in the leverage group (35% versus 30% in the entire population, and 38% versus 30% on average across investment styles). However, the difference is not extremely large, possibly due to the poor quality of the leverage data.

B.2 Aggregate Flows vs Style- and Fund-Specific Flows

In Table I of the paper, we find that aggregate flows to the hedge fund industry consistently predict lower hedge fund returns across all investment categories. Here, we examine how this relation is impacted when we include two additional flows variables in the baseline predictive regression. The first one measures style-specific flows as the value-weighted monthly percentage net inflows into each investment category, while the second one measures fund-specific flows as the monthly percentage net inflows into each fund.[6]

Comparing the relative importance of aggregate and style-specific flows, we observe in Table AIV that, on average, the style-specific flows variable exhibits the highest predictive ability. Specifically, it produces the largest proportions of funds with predictable returns and alphas ($\widehat{\pi}_R^-$ and $\widehat{\pi}_\alpha^-$ are equal to 19.8% and 20.5%, versus 15.0% and 17.2% for aggregate flows). This suggests that hedge fund performance is mostly sensitive to capacity constraints at the strategy level. Given the strong commonality in flows at the aggregate and style levels–the cross-fund average correlation is equal to 0.55–we expect aggregate flows to capture, at

[6] For this specification, we require each fund to have at least 36 monthly observations of its own flows variable, leading to a reduced sample of 5,868 funds between January 1994 and December 2008.

least partly, the impact of style-specific flows on performance. The results show that this is indeed the case. Specifically, the proportions, $\widehat{\pi}_R^-$ and $\widehat{\pi}_\alpha^-$, associated with aggregate flows decrease approximately by half when the style-specific flows variable is included in the regression (from 26.6% and 23.6% (baseline) to 15.0% and 17.2%). The fact that these proportions are still way above zero is consistent with the existence of capacity constraints at the industry level. Since many hedge funds operate in similar markets, it may be the case that flows invested in some categories do have spillover effects on the performance of funds outside these categories. Overall, the evidence suggests that the predictive ability of the aggregate flows variable comes from its ability to capture the impact of both global and style-specific capacity constraints.[7]

Turning to the analysis of fund-specific flows, we find that they contain predictive information that is orthogonal to that contained in aggregate and style-specific flows (the cross-fund average correlations are equal to -0.04% and -0.05%, respectively). Across the different categories, Table AIV shows that funds tend to have returns (alphas) that are negatively related to their fund-specific flows. While these results suggest capacity constraints also exist at the individual fund level, the magnitude of this effect is much lower than the one observed at the aggregate/style levels.

Please insert Table AIV here

C Out-of-Sample Analysis

C.1 Performance between 1997 and 2007

The recent financial crisis featured one of the most extreme variations in predictor values from their long-run levels, as well as the worst annual performance in the hedge fund industry.

[7] Using aggregate flows to proxy for style-specific flows may be useful when the number of funds within a given category is too low to produce accurate estimates of style-specific flows. This estimation issue may explain why there is no evidence of capacity constraints among the convertible bond funds (201 funds) based on style-specific flows ($\widehat{\pi}_R^- = 13\%$), while using aggregate flows shows a very different picture ($\widehat{\pi}_R^- = 39.1\%$).

To check whether the results shown in Table II of the paper are not only driven by this unique event, we recompute the results of the different strategies over the period January 1997 and December 2007. The results in Table AV (Panel A) show a large increase in performance across all strategies, highlighting the strong impact of the recent crisis. The largest improvement is observed for the unconditional strategy–its Fung-Hsieh alpha rises from 3.8% to 5.7% per year, and its Information Ratio goes up from 1.1 to 2.4 per year. As a result, none of the single-predictor strategies is able to dominate the unconditional strategy on a risk-adjusted basis (Information and Sharpe Ratios), once 2008 is excluded. Turning to the analysis of the combination strategy, we see that its superior performance is not driven by the recent crisis, as its estimated alpha, excess mean, Information and Sharpe Ratios are all statistically significantly higher than their unconditional counterparts (at the 10% level). Finally, Panels B and C confirm that the combination strategy still exhibits reasonable levels of turnover and autocorrelation, as well as low exposures to the FH risk factors.

Please insert Table AV here

C.2 Sensitivity Analysis

To determine whether the superior performance of the combination strategy is robust to alternative specifications, we perform a range of sensitivity checks reported in Panel A of Table AVI. First, removing the upper bound on the number of funds included in the portfolio (i.e., holding the top decile portfolio) leaves the results nearly unchanged. Second, our conclusions are robust to the inclusion of small funds (rather than imposing a AuM cutoff). Third, we assume in our baseline specification that when a fund stops reporting returns, its capital allocation is invested at the riskfree 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 is still positive. Fourth, 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 this information 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. Finally, 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.

Please insert Table AVI

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 market, size, book-to-market, and momentum four-factor model (obtained from Ken French's website), as well as extended versions of the Fung-Hsieh model in which we add the excess return of: 1) the Pastor and Stambaugh (2003) liquidity factor; 2) the emerging market index (proxied by the IFC emerging market index); 3) a trend-following strategy in the equity market (obtained from David Hsieh's website); 4) out-of-the-money S&P 500 call and put option-based factors proposed by Agarwal and Naik (2004). The results shown in Panel B confirm the superior performance of the combination strategy.

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Table AI

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 tradable risk factors. All statistics are computed using monthly observations between January 1994 and December 2008.

Panel A Fund Excess Returns

	Number(%)	Mean(Ann.)	Std(Ann.)	Skewness	Kurtosis
All Funds	8,376(100)	3.2%[-1.0,7.7]	11.1%[7.6,17.1]	-.16 [-.72,.26]	3.9 [3.0,5.7]
Long-Short	1,396(16.6)	5.0 [0.6,9.3]	13.5 [9.5,18.5]	-.08 [-.43,.28]	3.7 [2.9,4.7]
Market Neutral	230(2.7)	1.9 [-0.8,5.6]	7.8 [5.4,10.6]	-.16 [-.55,.22]	4.0 [3.1,5.6]
Managed Futures	831(9.9)	3.3 [-1.4,8.6]	15.2 [9.5,20.7]	.22 [-.02,.53]	3.5 [2.8,4.5]
Global Macro	237(2.8)	4.7 [0.5,9.0]	13.5 [9.4,18.4]	.12 [-.35,.46]	3.7 [3.1,4.8]
Emerging Markets	414(4.9)	5.1 [-0.1,11.3]	18.1 [11.8,24.4]	-.23 [-.64,.07]	3.4 [2.7,4.9]
Convertible Arb.	201(2.4)	2.2 [-1.8,5.1]	6.8 [4.2,10.4]	-.40 [-1.34,.05]	4.8 [3.5,8.2]
Event-Driven	278(3.3)	4.5 [0.8,8.9]	8.8 [5.9,13.2]	-.47 [-1.00,.14]	5.4 [4.0,7.6]
Fixed Income	270(3.2)	1.8 [-2.9,4.4]	9.0 [5.6,12.0]	-.61 [-1.92,.18]	6.3 [4.0,10.5]
Funds of Funds	2,274(27.1)	0.7 [-3.1,3.6]	8.5 [6.1,10.7]	-.62 [-1.24,-.10]	4.4 [3.4,6.6]
Multi-Strategy	723(8.6)	5.8 [1.7,11.3]	14.8 [9.5,22.2]	.12 [-.21,.44]	3.3 [2.6,4.8]

Panel B Predictors

			Autocorr.		Correlation matrix		
	Mean(Mon.)	Std(Mon.)	94-07	94-08	Dividend	VIX	Agg. Flows
Default Spread	0.9%	0.3%	0.95	1.10	.21	.55	-.13
Dividend Yield	2.0	0.4	0.97	1.00		-.11	-.36
VIX (Volatility)	20.2	7.7	0.84	0.85			-.16
Aggregate Flows	0.7	2.1	0.23	0.34			

Table AI

Descriptive Statistics (Continued)

Panel C Risk Factor Returns

			Correlation matrix					
	Mean(Ann.)	Std(Ann.)	Size	Term	Def.	T. Bond	T. Cur.	T. Com.
Equity Market	3.7%	14.9%	-.02	-.12	.54	-.17	-.19	-.15
Equity Size	-2.1	12.9		-.15	.20	-.05	.01	-.02
Bond Term	-3.1	6.4			-.08	.11	.12	.07
Bond Default	5.6	7.0				-.09	-.23	-.16
Trend Bond	-11.1	52.0					.18	.17
Trend Currency	6.9	69.0						.36
Trend Commodity	-1.1	48.8						

Table AII
Fund Illiquidity Profiles

We determine the hedge fund illiquidity profiles in the entire population, and across investment categories. In the first row (Return), we show the estimated proportions of funds having reported returns, $r^0_{i,t+1}$, that are negatively and positively autocorrelated at the first two lags (- +). The third row-element (Test MA(2)) displays the estimated proportion of funds for which the MA(2) specification is rejected. Specifically, we test the null hypothesis that the third-order autocorrelation coefficient is equal to zero (using a Bartlett's approximation to compute the variance of the estimated coefficient). We also report the cross-sectional mean and standard deviation of the MA(2) parameters, $\widehat{\theta}_{i,0}$, $\widehat{\theta}_{i,1}$ and $\widehat{\theta}_{i,2}$, obtained from the moment matching technique shown in Equation (A14). Finally, the second row (Residual) reports the same information using the fund reported residuals, $e^0_{i,t+1}$. All statistics are computed using monthly observations between January 1994 and December 2008.

	Autocorrelation					Illiquidity Profiles					
	First-order		Second-order		Test	$\widehat{\theta}_{i,0}$		$\widehat{\theta}_{i,1}$		$\widehat{\theta}_{i,2}$	
	−	+	−	+	MA(2)	Mean	Std	Mean	Std	Mean	Std
					All Funds						
Return	0.0	50.1	1.5	21.5	3.2	0.86	0.23	0.12	0.15	0.02	0.16
Residual	1.0	23.3	2.3	6.9	0.2	0.97	0.22	0.03	0.16	0.00	0.15
					Long-Short Equity						
Return	0.0	58.2	0.0	16.7	5.0	0.86	0.20	0.12	0.13	0.02	0.14
Residual	0.0	27.9	0.0	12.7	3.2	0.95	0.20	0.03	0.15	0.01	0.14
					Market Neutral						
Return	0.0	37.0	0.0	12.2	0.9	0.93	0.25	0.07	0.17	0.00	0.15
Residual	1.9	23.5	5.8	7.9	1.9	0.97	0.22	0.03	0.17	0.00	0.17
					Managed Futures						
Return	0.0	15.8	16.2	3.2	6.9	0.99	0.22	0.05	0.16	-0.04	0.16
Residual	1.0	11.5	13.0	0.0	1.7	1.05	0.22	0.01	0.16	-0.05	0.16
					Global Macro						
Return	0.0	40.1	20.9	6.8	1.8	0.95	0.22	0.09	0.16	-0.04	0.16
Residual	0.0	24.0	21.9	0.0	0.0	1.04	0.23	0.03	0.17	-0.06	0.16
					Emerging Market						
Return	0.0	69.0	0.0	30.6	0.0	0.78	0.20	0.15	0.12	0.07	0.14
Residual	0.7	39.5	0.0	7.1	0.0	0.94	0.22	0.05	0.16	0.01	0.14
					Convertible Arbitrage						
Return	0.0	88.8	0.0	33.9	23.1	0.67	0.20	0.24	0.11	0.09	0.16
Residual	0.0	63.5	6.2	28.6	11.4	0.81	0.21	0.16	0.14	0.02	0.15

Table AII

Fund Illiquidity Profiles (Continued)

	Autocorrelation					Illiquidity Profiles					
	First-order		Second-order		Test	$\widehat{\theta}_{i,0}$		$\widehat{\theta}_{i,1}$		$\widehat{\theta}_{i,2}$	
	−	+	−	+	MA(2)	Mean	Std	Mean	Std	Mean	Std
					Event-Driven						
Return	0.0	74.8	0.0	36.7	17.7	0.77	0.22	0.16	0.14	0.07	0.14
Residual	0.0	35.7	0.0	27.2	0.0	0.89	0.19	0.07	0.15	0.04	0.13
					Fixed Income						
Return	0.0	66.3	2.0	27.1	5.4	0.79	0.27	0.16	0.18	0.05	0.17
Residual	0.0	35.4	2.9	14.2	0.0	0.93	0.23	0.06	0.17	0.01	0.17
					Funds of Funds						
Return	0.0	66.3	2.0	26.9	1.3	0.78	0.22	0.15	0.13	0.08	0.14
Residual	1.8	20.9	0.0	0.0	0.0	0.98	0.21	0.02	0.17	0.00	0.13
					Multi-Strategy						
Return	0.0	20.4	21.8	7.8	8.9	0.97	0.25	0.08	0.16	-0.05	0.17
Residual	2.5	9.8	23.9	2.9	6.5	1.05	0.24	0.01	0.17	-0.06	0.17

Table AIII

Alternative Leverage Indicators

We compare the predictive ability of the dividend yield and alternative measures of leverage in the entire population and across the different investment categories. Considering the initial predictive regression that includes the default spread, the dividend yield, the VIX, and aggregate flows (Baseline Specification), we replace the dividend yield with: 1) the past annual return of the Prime Broker Index (PBI) (Specification 1); 2) the TED spread, measured as the difference between the 3-month Eurodollar deposit rate and the 3-month Treasury Bill. In the first row (Return), we report, for each predictor, 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. 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. In the second row (Alpha), we repeat the procedure using the estimated coefficients in the predictive alpha regression. All statistics are computed using monthly data between January 1994 and December 2008.

	Baseline Specification Dividend Yield			Specification 1 Prime Broker Index			Specification 2 TED Spread		
	−	+	Slope Coeff.	−	+	Slope Coeff.	−	+	Slope Coeff.
				All Funds					
Return	34.0	2.1	-.22[-.58,.12]	0.0	26.7	.21[-.08,.54]	32.8	5.6	-.21[-.68,.17]
Alpha	35.9	1.6	-.23[-.58,.09]	0.0	32.0	.20[-.08,.47]	30.0	5.1	-.18[-.59,.18]
				Long-Short Equity					
Return	32.5	2.1	-.24[-.67,.18]	0.0	24.6	.28[-.06,.69]	31.3	13.9	-.16[-.72,.39]
Alpha	37.8	2.1	-.27[-.70,.10]	0.0	27.7	.22[-.10,.54]	20.7	14.1	-.05[-.50,.39]
				Market Neutral					
Return	22.4	0.0	-.13[-.36,.10]	2.0	15.8	.07[-.16,.23]	22.5	15.9	-.02[-.34,.26]
Alpha	24.2	3.5	-.12[-.40,.13]	0.9	21.5	.09[-.08,.29]	22.8	14.0	-.05[-.42,.25]
				Managed Futures					
Return	5.0	11.3	.03[-.39,.47]	4.0	2.6	.01[-.34,.40]	6.6	0.0	-.10[-.49,.22]
Alpha	7.9	11.3	.06[-.37,.48]	0.0	7.3	.04[-.28,.36]	16.5	2.2	-.12[-.53,.25]
				Global Macro					
Return	24.8	4.1	-.18[-.72,.20]	0.0	34.6	.23[-.16,.69]	13.1	9.7	-.02[-.48,.34]
Alpha	31.2	0.0	-.25[-.76,.12]	0.2	38.5	.23[-.11,.68]	15.9	4.6	-.14[-.55,.25]
				Emerging Market					
Return	38.3	0.0	-.49[-1.16,-.02]	0.0	39.8	.36[-.08,.97]	48.8	1.1	-.61[-1.37,.02]
Alpha	43.8	0.0	-.46[-1.02,.02]	3.7	24.2	.17[-.23,.68]	30.1	0.0	-.35[-.95,.06]
				Convertible Arbitrage					
Return	52.9	2.8	-.25[-.52,.01]	0.0	64.6	.36[.17,.68]	36.9	9.5	-.11[-.77,.14]
Alpha	50.2	0.0	-.25[-.57,.02]	0.0	62.9	.33[.12,.60]	33.1	13.3	-.08[-.54,.17]

Table AIII

Alternative Leverage Indicators (Continued)

	Baseline Specification Dividend Yield			Specification 1 Prime Broker Index			Specification 2 TED Spread		
	−	+	Slope Coeff.	−	+	Slope Coeff.	−	+	Slope Coeff.
				Even-Driven					
Return	42.4	0.0	-.22[-.55,.02]	0.0	42.4	.26[.04,.58]	44.2	0.8	-.29[-.77,.05]
Alpha	40.2	0.0	-.19[-.56,.03]	0.0	34.6	.18[-.02,.46]	36.6	3.6	-.20[-.50,.07]
				Fixed Income					
Return	36.4	7.1	-.12[-.41,.12]	7.1	25.6	.09[-.12,.38]	39.9	2.0	-.21[-.71,.05]
Alpha	32.0	9.4	-.11[-.40,.14]	7.7	24.4	.06[-.10,.35]	32.8	0.0	-.15[-.61,.04]
				Funds of Funds					
Return	46.2	0.0	-.31[-.56,.-09]	0.0	41.5	.26[.05,.49]	48.1	2.3	-.34[-.67,.01]
Alpha	46.7	0.0	-.28[-.54,.07]	0.0	53.4	.26[.09,.44]	43.8	0.8	-.26[-.61,.01]
				Multi-Strategy					
Return	29.6	7.7	-.15[-.55,.31]	3.9	17.2	.10[-.30,.42]	19.1	5.1	-.09[-.52,.31]
Alpha	24.4	2.1	-.20[-.58,.18]	0.0	19.3	.16[-.19,.50]	32.4	1.2	-.27[-.79,.14]

Table AIV

Aggregate, Style-Specific, and Fund-Specific Flows

We compare the predictive ability of hedge fund flows at the aggregate, investment style, and individual fund levels for different investment categories. Considering the initial predictive regression that includes the default spread, the dividend yield, the VIX, and aggregate flows (Baseline Specification), we add two additional predictors: 1) style-specific flows, measured as the value-weighted monthly percentage net inflows into each style; 2) fund-specific flows, measured as the monthly percentage net inflows into each fund. In the first row (Return), we report, for each predictor, 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, $\bar{b}_j$, and 25-75% quantiles (in brackets) of the (bias-corrected) estimated slope coefficient. 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. In the second row (Alpha), we repeat the procedure using the estimated coefficients in the predictive alpha regression. All statistics are computed using monthly data between January 1994 and December 2008.

	Baseline Specification			Specification 1								
	Aggregate Flows			Aggregate Flows			Style-specific Flows			Fund-specific Flows		
	−	+	Slope Coeff.	−	+	Slope Coeff.	−	+	Slope Coeff.	−	+	Slope Coeff.
	Average across Investment Styles											
Return	26.6	2.3	-.20[-.57,.06]	15.0	4.7	-.05[-.40,.24]	19.8	6.7	-.14[-.53,.17]	7.7	3.7	-.02[-.28,.23]
Alpha	23.6	3.0	-.16[-.53,.09]	17.2	4.7	-.09[-.45,.19]	20.5	7.2	-.11[-.48,.19]	9.4	7.7	-.01[-.26,.26]
	Long-Short Equity											
Return	28.4	0.0	-.30[-.79,.05]	10.0	8.0	-.02[-.42,.38]	34.5	0.0	-.39[-.91,-.03]	12.1	6.8	-.03[-.38,.30]
Alpha	25.6	0.0	-.19[-.62,.14]	16.2	0.0	-.16[-.52,.17]	20.5	0.5	-.15[-.59,.19]	9.0	6.7	-.03[-.33,.29]
	Market Neutral											
Return	14.6	2.8	-.05[-.31,.15]	10.5	0.0	-.05[-.30,.17]	14.5	12.5	.02[-.24,.22]	6.9	2.9	-.02[-.20,.15]
Alpha	24.0	9.6	-.06[-.35,.20]	25.0	5.3	-.12[-.33,.16]	7.9	17.4	.04[-.18,.26]	22.4	9.3	-.05[-.28,.19]
	Managed Futures											
Return	5.0	2.7	-.02[-.39,.29]	0.0	15.8	.13[-.22,.56]	29.8	0.0	-.34[-.88,.01]	4.1	3.7	.02[-.30,.33]
Alpha	11.6	0.7	-.12[-.50,.19]	3.5	13.9	.05[-.28,.47]	32.2	0.0	-.28[-.77,.04]	4.5	7.8	.02[-.26,.34]
	Global Macro											
Return	29.4	5.0	-.25[-.66,.21]	18.9	7.5	-.01[-.60,.33]	20.1	6.0	-.12[-.57,.31]	3.1	3.5	-.04[-.30,.32]
Alpha	23.4	5.8	-.12[-.62,.22]	14.3	6.1	-.06[-.51,.25]	18.9	5.3	-.10[-.64,.30]	12.7	6.9	-.05[-.38,.31]

Table AIV

Aggregate, Style-Specific, and Fund-Specific Flows (Continued)

	Baseline Specification			Specification 1								
	Aggregate Flows			Aggregate Flows			Style-specific Flows			Fund-specific Flows		
	−	+	Slope Coeff.	−	+	Slope Coeff.	−	+	Slope Coeff.	−	+	Slope Coeff.
Emerging Market												
Return	36.7	0.0	-.40[-.98,.04]	16.1	0.0	-.15[-.60,.33]	29.6	0.0	-.28[-.91,.16]	7.0	10.1	.00[-.35,.43]
Alpha	23.4	0.0	-.27[-.84,.10]	29.8	0.0	-.33[-1.20,.04]	17.8	13.9	-.00[-.53,.48]	6.9	21.0	.08[-.31,.52]
Convertible Arbitrage												
Return	39.1	0.0	-.14[-.35,.00]	41.9	0.5	-.19[-.34,-.03]	13.0	15.3	.02[-.19,.21]	6.0	3.8	-.03[-.18,.11]
Alpha	33.3	0.0	-.12[-.24,.05]	37.6	0.0	-.16[-.41,-.03]	9.1	24.7	.06[-.15,.26]	7.0	9.2	.02[-.11,.16]
Event-Driven												
Return	41.0	0.6	-.16[-.45,.07]	25.1	3.6	-.06[-.41,.12]	17.0	0.0	-.13[-.37,.03]	13.5	0.0	-.03[-.27,.11]
Alpha	19.2	0.0	-.11[-.36,.07]	16.3	4.3	-.01[-.32,.13]	32.4	0.2	-.14[-.34,.06]	11.4	0.3	-.03[-.21,.10]
Fixed Income												
Return	16.7	12.2	-.02[-.32,.26]	8.7	3.7	-.01[-.26,.15]	0.4	24.2	.08[-.12,.40]	9.1	0.0	-.04[-.23,.10]
Alpha	18.2	14.3	-.02[-.30,.27]	3.4	13.3	.02[-.15,.20]	16.2	10.3	-.03[-.28,.20]	9.7	4.7	.00[-.20,.15]
Funds of Funds												
Return	40.5	0.0	-.24[-.59,-.01]	12.9	0.0	-.11[-.43,.12]	24.7	9.0	-.09[-.53,.21]	7.3	4.2	-.02[-.21,.17]
Alpha	34.8	0.0	-.19[-.56,.00]	18.4	1.0	-.07[-.36,.17]	26.3	0.0	-.23[-.63,.02]	0.9	6.6	.02[-.15,.20]
Multi-Strategy												
Return	14.8	0.0	-.12[-.58,.17]	6.4	7.9	.02[-.41,.43]	13.8	0.0	-.13[-.61,.22]	7.8	2.1	-.03[-.37,.32]
Alpha	22.1	0.0	-.19[-.60,.12]	7.5	3.2	-.01[-.46,.35]	24.0	0.0	-.24[-.72,.13]	9.5	4.7	-.04[-.34,.32]

Table AV

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. 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-order 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 (January 1997-December 2007)

	Fung-Hsieh Alpha (Ann.)			Excess Return (Ann.)		
	$\widehat{\alpha}$	$\widehat{\sigma}_{res}$	IR=$\widehat{\alpha}/\widehat{\sigma}_{res}$	$\widehat{\mu}$	$\widehat{\sigma}_{tot}$	SR=$\widehat{\mu}/\widehat{\sigma}_{tot}$
Unconditional	5.7%	2.4%	2.4	6.8%	3.9%	1.7
Single-Predic.						
Default Spread	7.5(.06)	3.6	2.1(.85)	8.6(.07)	5.3	1.6(.81)
Dividend Yield	7.9(.01)	3.6	2.2(.81)	8.9(.02)	5.8	1.5(.89)
VIX (Volatility)	6.3(.17)	3.4	1.8(.95)	7.7(.05)	5.0	1.6(.85)
Aggregate Flows	5.5(.59)	2.7	2.1(.88)	7.2(.28)	4.4	1.6(.80)
Multi-Predic.	5.1(.64)	3.7	1.4(.99)	6.1(.74)	4.8	1.3(.97)
Combination	6.9(.01)	2.6	2.7(.06)	8.4(.00)	4.5	1.9(.09)
Index (VW)	3.8(.96)	3.9	1.0(1.0)	5.5(.98)	5.3	1.0(1.0)
Index (EW)	4.3(.96)	3.2	1.3(1.0)	5.6(.96)	5.4	1.0(1.0)

Table AV
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[63,72]	63%[55,68]	.15	-.05	12.5%	7.8%	7.1%
Single-Predic.							
Default Spread	67[60,72]	82[74,89]	.26(.02)	.02(.26)	12.6	8.8	5.6
Dividend Yield	69[62,72]	73[64,78]	.21(.08)	.02(.11)	12.9	5.9	6.1
VIX (Volatility)	69[61,72]	70[62,75]	.09(.94)	-.02(.07)	14.1	8.7	5.0
Aggregate Flows	69[61,72]	70[59,77]	.19(.18)	-.08(.87)	12.0	8.5	7.7
Multi-Predic.	69[58,72]	87[84,95]	.15(.47)	-.02(.27)	11.8	11.6	5.8
Combination	69[62,72]	67[62,70]	.19(.10)	.00(.15)	11.0	7.5	7.4

Panel C Sensitivity to the Fung-Hsieh Risk Factors

	Market	Size	Term	Default	T.Bond	T.Cur.	T.Com.	R^2
Unconditional	.12	.08	.08	.09	-.01	.00	.01	51.3%
Single-Predic.								
Default Spread	.18(.00)	.11(.11)	.04(.80)	.04(.85)	-.01(.09)	.00(.87)	.00(.93)	40.3
Dividend Yield	.19(.00)	.15(.00)	.17(.01)	.07(.73)	-.02(.84)	.01(.32)	.01(.26)	48.7
VIX (Volatility)	.15(.04)	.06(.87)	.08(.46)	.11(.31)	-.01(.63)	.01(.16)	.02(.00)	39.0
Aggregate Flows	.12(.52)	.08(.41)	.04(.91)	.16(.00)	-.01(.24)	.00(.60)	.00(.92)	49.5
Multi-Predic.	.10(.67)	.10(.16)	.08(.45)	.10(.45)	-.01(.25)	.01(.45)	.01(.29)	27.6
Combination	.14(.03)	.09(.06)	.06(.74)	.11(.26)	-.02(.82)	.00(.81)	.01(.78)	53.2

Table AVI

Sensitivity Analysis

In Panel A, we examine whether the performance of the unconditional and combination strategies is sensitive to changes in specification. We consider the following changes: 1) no upper bound on the maximum number of funds included in the portfolio (i.e., holding the decile portfolio); 2) no AuM cutoff; 3) -25% monthly return penalty when a fund has a missing observation; 4) returns over the previous month are not available in the hedge fund databases; 5) three-month notice period prior to withdrawal. In each case, we report the (annualized) Fung-Hsieh alpha, $\widehat{\alpha}$, Information Ratio, IR, excess mean, $\widehat{\mu}$, and Sharpe Ratio, SR. In Panel B, we examine whether performance is sensitive to changes in the asset pricing model. We consider the following models: 1) four-factor model (market, size, value, and momemtum factors); and the Fung-Hsieh model in addition to 2) a liquidity factor; 3) an emerging market factor; 4) a trend-following factor in the equity market; 4) out-of-the-money S&P 500 call and put option-based factors. 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). All statistics are computed using monthly observations between January 1994 and December 2008.

Panel A Changes in Specification

	Unconditional				Combination			
	$\widehat{\alpha}$	IR	$\widehat{\mu}$	SR	$\widehat{\alpha}$	IR	$\widehat{\mu}$	SR
No Upper Bound (Decile)	3.5	1.0	4.8	0.9	5.3	1.6(.00)	6.6	1.2(.00)
No AuM Cutoff	5.8	2.1	6.4	1.4	6.1	2.3(.08)	6.9	1.5(.21)
-25% Missing Return Penalty	1.0	0.3	2.2	0.4	2.8	0.8(.00)	4.0	0.8(.00)
1 Month-Reporting Lag	4.0	1.2	5.0	1.0	4.8	1.5(.07)	6.0	1.2(.09)
3 Month-Notice Period	3.0	0.9	4.4	0.9	3.8	1.3(.06)	5.1	1.2(.01)

Panel B Changes in Asset Pricing Model

	Unconditional				Combination			
	$\widehat{\alpha}$	IR	$\widehat{\mu}$	SR	$\widehat{\alpha}$	IR	$\widehat{\mu}$	SR
Four Factors	3.3	1.0	-	-	5.0	1.7(.01)	-	-
FH Factors+Liquidity	3.6	1.1	-	-	5.3	1.8(.00)	-	-
FH Factors+Emerging Market	3.9	1.3	-	-	5.5	2.0(.00)	-	-
FH Factors+Equity Straddle	4.0	1.2	-	-	5.8	1.9(.00)	-	-
FH Factors+Option Factors	3.5	1.1	-	-	5.2	1.7(.01)	-	-