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Hedge Fund Performance under Misspecified Models

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Hedge Fund Performance under Misspecified Models[☆]

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Abstract

We develop a new approach for evaluating performance across hedge funds. Our approach allows for performance comparisons between models that are misspecified – a common feature given the numerous factors that drive hedge fund returns. The empirical results show that the standard models used in previous work omit similar factors because they (i) perform exactly like the CAPM, and (ii) produce large and positive alphas. In contrast, we observe a large and statistically significant decrease in performance with a new model formed with alternative factors that capture variance, correlation, liquidity, betting-against-beta, carry, and time-series momentum strategies. Overall, the results suggest that the average returns of hedge funds are largely explained by mechanical trading strategies.

Keywords: Hedge funds, performance, model misspecification, large panel

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1. Introduction

Over the past three decades, the growth of the hedge fund industry has been outstanding. Its total size has increased from approximately $40 billion in 1990 to close to $3 trillion at the end of 2016 (see Getmansky, Lee, and Lo, 2015). This strong demand from investors such as high-net-worth individuals and pension funds reflects the widely held view that hedge funds deliver high risk-adjusted returns, also called alphas. This view is supported by the arguments that hedge fund managers are more sophisticated, less constrained, and more incentivized to perform than mutual fund managers. Consistent with these arguments, the previous literature documents a strong and positive hedge fund performance—for instance, Kosowski, Naik, and Teo (2007) find a cross-sectional average alpha of 5% per year using the popular model of Fung and Hsieh (2004).[1]

One concern with such a high level of performance is that it is too good to be true. As discussed by Lhabitant (2007) and Pedersen (2015), hedge funds follow complex investment strategies across multiple countries and asset classes. This complexity suggests that all hedge fund models are misspecified as they fail to include all the factors required to form an appropriate benchmark (*e.g.*, Bollen, 2013). As a result, the estimated performance is likely to be inflated – to the extent that hedge funds load on "hidden" factors to boost average returns, their estimated alphas are contaminated by the return premia associated with such factors.

Model misspecification calls for an evaluation of performance across multiple models. This comparison analysis is important for several reasons. First, it describes how performance varies across models. In particular, it evaluates the importance of using models that are more complex than the CAPM – a choice commonly made in the hedge fund literature (see Getmansky, Lee, and Lo, 2015). Second, it is likely to provide a sharper measurement of the true performance delivered

[1] A non-exhaustive list of papers that document a positive hedge fund performance includes Ackermann, McEnally, and Ravenscraft (1999), Capocci and Hübner (2004), Buraschi, Kosowski, and Trojani (2014), Diez de los Rios and Garcia (2010), Getmansky, Lee, and Lo (2015), Liang (1999). More recently, Chen, Cliff, and Zhao (2017) estimate the entire alpha distribution and find that only 9% of the hedge funds exhibit negative alphas – a number that is substantially lower than the one documented for mutual funds (see Barras, Scaillet, and Wermers, 2010; Harvey and Liu, 2018).

by hedge funds. Because existing models include different sets of factors, some are likely to produce alphas that are less affected by omitted factors. Finally, comparing models allows us to examine the marginal contribution of different hedge fund factors. This information is useful to construct future models that are less prone to misspecification.

In this paper, we develop a novel approach for evaluating hedge fund performance with multiple models. This approach has three distinguishing features. First, it explicitly accounts for the possibility that the different models are misspecified. Second, it provides an estimation of the entire alpha distribution to capture the suspected large heterogeneity in hedge fund performance. The estimation procedure is simple – it uses as only inputs the estimated fund alphas to compute several cross-sectional characteristics including the moments, the proportion of funds with positive alphas, and the quantiles in the tails of the distribution. Third, it comes with a full-fledged asymptotic theory which determines the properties of each estimated characteristic as the number of observations T and the number of funds n grow large. This theoretical framework allows us to formally compare performance across models.

On the theory side, we show that misspecification largely changes the properties of the estimated alpha distribution. We document two main changes compared to the correctly-specified case examined by Barras, Gagliardini, and Scaillet (2020). First, the estimated characteristics are less precisely estimated because they converge at a rate equal to $\sqrt{T}$ instead of $\sqrt{n}$. The convergence rate is therefore significantly slower because we have thousands of funds, but only a few hundred of observations (i.e., n is much larger than T). This result seems surprising because the characteristics are all computed as cross-sectional averages (*i.e.*, we sum across funds, not over time). Second, the estimated characteristics do not require an error-in-variable (EIV) bias adjustment, even though they are computed with estimated alphas (instead of the true values). Intuitively, both differences arise because the estimated characteristics ultimately depend on the omitted factors. This dependence generates a larger estimation variance that dwarfs the EIV bias in magnitude, making any adjustment unnecessary.

We apply our new approach to the monthly returns of more than 13,000 hedge funds collected from five different data providers (BarclayHedge, Eurekahedge, HFR, Morningstar, and TASS) over the period 1994–2016 (276 observations). Following the classification of Joenväärä, Kauppila, Kosowski, and Tolonen (2019), we sort all funds into three broad hedge fund categories: (i) equity funds (long-short, market neutral), (ii) macro funds (global macro, CTA funds), and (iii) arbitrage funds (relative value, event-driven). Using this combined database, we begin our empirical analysis by measuring the performance of individual funds using 7 standard models in previous work: (i) the CAPM, (ii) the 3-factor model of Fama and French (1993), (iii) the 3-factor model of Asness, Moskowitz, and Pedersen (2013), (iv) the 4-factor model of Carhart (1997), (v) the 5-factor models of Fama and French (2015), (vi) the 6-factor model of Hasanhodzic and Lo (2007), and (vii) the 7-factor model of Fung and Hsieh (2004).

We uncover a striking similarity in performance across all standard models. This similarity extends beyond the average to all the characteristics of the alpha distribution (variance, proportion, quantiles). Our formal comparison tests confirm that the standard models produce the same performance evaluation. For instance, none of the estimated pairwise differences in mean is significant at the 1%-level. Consistent with the previous literature, we also find that the hedge fund performance measured with the standard models is economically large – The alpha is around 2.50% per year on average and is positive for more than 65% of the funds in the population.

We then show that a plausible explanation for the above results is misspecification. We find that the average R^2 ranges between 20% and 30% across the different models, leaving plenty of room for omitted factors. Consistent with this intuition, the diagnostic criterion of Gagliardini, Ossola, and Scaillet (2019) concludes that the fund residuals are strongly correlated because they all depend on common omitted factors. These results provide a motivation for examining a broader set of hedge fund factors – a point forcefully made by the recent paper by Joenväärä, Kauppila, Kosowski, and Tolonen (2019) which highlights “the need for an updated benchmark model that reflects the post–2004 literature”.

To address this issue, we consider a set of 13 alternative factors examined in the recent asset pricing literature. These factors are easily interpretable as the excess returns of mechanical trading strategies that hedge funds can potentially follow. Specifically, we include: (i) the correlation and variance factors inferred from the prices of equity options (Buraschi, Kosowski, and Trojani, 2014), (ii) the market liquidity factor of Pástor and Stambaugh (2003), (iii) the betting-against-beta (BAB) factor of Frazzini and Pedersen (2014), (iv) a set of carry strategies applied to multiple asset classes (Koijen, Moskowitz, Pedersen, and Vrugt, 2018), and (v) a set of time-series (TS) momentum strategies applied to multiple asset classes (Moskowitz, Ooi, and Pedersen, 2012).[2]

Our analysis reveals several insights about the exposures of hedge funds to these alternative factors. First, we find that the majority of the funds exhibit positive betas on all factors except one (currency carry). Therefore, this finding supports the view that hedge funds load on "hidden" factors to increase their average returns. Second, we find that negative-alpha funds tend to have higher betas – possibly because they want to hide their lack of skill by boosting their average returns. Finally, we find little evidence that hedge funds take correlated exposures across factors. This implies that individual funds do not take advantage of the diversification benefits that arise from the low correlation between the different trading strategies.

Consistent with economic intuition, the three hedge fund categories are sensitive to different trading strategies. The returns of equity funds vary with unexpected changes in correlation and variance, consistent with the idea that such changes limit the effectiveness of their hedging strategies (Buraschi, Kosowski, and Trojani, 2014). Equity funds also load on TS momentum which suggest that they follow this strategy to determine their overall allocation across international equity markets. Turning to macro funds, we find that carry and TS momentum play a central role – macro funds earn a large return premium from these strategies in the fixed income and commodity markets. Finally, arbitrage funds are primarily exposed to variance risk. This exposure likely arises

[2]As explained by Moskowitz, Ooi, and Pedersen (2012), TS momentum favors assets with high returns relative to their own average. Therefore, it differs from traditional momentum which favors assets with high returns relative to the average across the other assets (see Jegadeesh and Titman, 1993).

because these funds commonly use option-based strategies – classic examples involve mortgage and volatility arbitrage in the fixed-income market (see Duarte, Longstaff, and Yu, 2006).

We conclude our empirical analysis by proposing a new model for evaluating hedge fund performance. We construct a seven-factor model that includes the market, correlation, variance, liquidity, BAB, global carry, and global TS momentum factors. We find that this new model dramatically reduces the overall performance of the hedge fund industry. The average alpha turns negative at -0.07% per year, which represents a statistically significant reduction of 2.86% relative the Fung-Hsieh model. Similarly, the proportion of positive-alpha funds decreases sharply from 69.00% to 51.85%. In addition, the new model produces a significantly fatter left tail as it controls for the aggressive exposures that poorly performing funds take on the alternative factors. The 10%-quantile is equal to -11.23% per year versus -6.65% with the Fung-Hsieh model. All these results hold across multiple investment categories and subperiods. Overall, the empirical evidence suggests that the seemingly strong performance of hedge funds can be largely explained by a set of mechanical trading strategies.

The remainder of the paper is as follows. Section 2 presents our framework for evaluating hedge fund performance. Section 3 describes our novel estimation approach. Section 4 presents the hedge fund dataset and factors. Section 5 contains the empirical analysis, and Section 6 concludes. The appendix provides additional information regarding the methodology, the data, and the empirical results.

2. Hedge Fund Performance and Model Misspecification

2.1. Hedge Fund Performance

2.1.1. The Benefits of Performance Evaluation

The objective of this paper is to evaluate the performance of individual hedge funds. In other words, we examine whether the hedge fund industry provides investors with superior returns net of fees and trading costs or, more simply, positive alphas. Our framework exclusively focuses on performance and not skill. Whereas the two notions are commonly used interchangeably, they differ in important ways – a point forcefully made by Berk and van Binsbergen (2015). Broadly speaking, skill is defined from the viewpoint of funds, *i.e.*, it measures whether hedge funds have unique investment skills that allow them to extract value from capital markets. In contrast, performance is defined from the viewpoint of investors, *i.e.*, it measures whether the value created by the funds, if any, is passed on to them.

Performance evaluation provides a separation between the alpha and beta components of hedge fund returns. The alpha captures the benefits of active management – investing in a positive alpha fund improves the risk-return trade-off of the portfolio (Treynor and Fisher, 1973). The beta component captures the fund's exposure to common hedge fund factors and allows the investor to manage the overall risk of the portfolio.

Measuring performance is particularly important for hedge funds for several reasons. First, there is a commonly held view that hedge funds achieve positive returns because they load on "hidden" sources of risk orthogonal to traditional equity factors. A proper performance analysis can determine how many funds produce negative alphas and charge excessive fees to their investors. Second, the performance analysis allows for an investor-specific interpretation of the beta component of hedge fund returns. As noted by Cochrane (2013) and Pedersen (2015), some hedge fund trading strategies are not based on superior information but require technical knowledge. For instance, implementing a momentum strategy requires trading skills to mitigate the impact of transaction costs. The hedge fund investor can isolate the trading strategies that she finds harder to replicate, and attribute a positive alpha to hedge funds if they are able to implement them at a lower cost.

2.1.2. Measuring Performance

The basic idea for measuring performance is straightforward. For each fund i in the population, we measure its performance using the net alpha α_i^*:

$$\alpha_i^* = E[r_{i,t}] - E[r_{i,t}^B] = E[r_{i,t}] - \beta_i^{*\prime} E[f_t] = E[r_{i,t}] - \beta_i^{*\prime}\lambda\,, \tag{1}$$

where $r_{i,t}$ is the fund excess return net of trading costs and fees, and $r_{i,t}^B$ is the excess return of the benchmark portfolio assigned to fund i. The benchmark is defined as a linear combination of a set of mechanical trading strategies whose mean vector $E[f_t]$ is equal to the average excess return vector λ since the factors are tradable. We define each strategy such that its return premium is positive (*i.e.*, $\lambda > 0$). The positive premia associated with these strategies could be a compensation for bearing systematic risk, or the outcome of imperfect risk sharing driven by segmentation or behavioral biases. In this paper, we remain agnostic on this issue – our objective is simply to avoid giving credit to the fund for following mechanical strategies that can be directly implemented by investors.

If we know the correct model, we can estimate the alpha of each fund from the following time-series regression:

$$r_{i,t} = \alpha_i^* + \beta_i^{*\prime} f_t + \varepsilon_{i,t}^*\,, \tag{2}$$

where $\varepsilon_{i,t}^*$ denotes the fund residual term. Equation (2) is interpreted as a random coefficient model (*e.g.*, Hsiao, 2003) in which the fund alpha α_i^* is not a fixed parameter, but a random realization from a continuum of funds. Under this sampling scheme, we can invoke cross-sectional limits to infer the entire cross-sectional alpha distribution and its characteristics such as the mean, variance, and quantiles (see Gagliardini, Ossola, and Scaillet, 2016; Barras, Gagliardini, and Scaillet, 2020).

2.2. *Model Misspecification*

2.2.1. *The Impact of Model Misspecification*

In practice, measuring hedge fund performance is challenging because of model misspecification. This issue arises because hedge funds follow a wide range of strategies. They invest in many asset classes (equities, bonds, and derivatives) and trade in both developed and emerging markets (*e.g.* Lhabitant, 2007; Pedersen, 2015). They also engage in dynamic trading strategies which capture the time-variation in betas due to changes in economic and leverage conditions (see Ang, Gorovyy, and van Inwegen, 2011; Patton and Ramadorai, 2013).[3] As a result, any model used for benchmarking hedge fund performance is likely to be misspecified as it only captures a limited number of trading strategies.

To elaborate, suppose that instead of using the correct model in Equation (2), we work with a misspecified model that only includes the factors $f_{I,t}$, but omits the factors $f_{O,t}$ (with $f_t = (f'_{I,t}, f'_{O,t})'$):

$$r_{i,t} = \alpha_i + \beta'_i f_{I,t} + \varepsilon_{i,t} \,. \tag{3}$$

The fund alpha α_i obtained with the misspecified model in Equation (3) typically differs from the true alpha α^*_i. To see this point, we can write the omitted factors as: $f_{O,t} = \alpha_O + \Psi_{O,I} f_{I,t} + u_{O,t}$, where $\Psi_{O,I}$ is the matrix of slope coefficients, $u_{O,t}$ is the vector of factor residuals, and α_O is the vector of factor alphas – that is, the vector of return premia of the omitted factors left unexplained by the included factors: $\alpha_O = \lambda_O - \Psi_{O,I}\lambda_I$. Replacing λ with $(\lambda'_I, \lambda'_O)'$ and β^*_i with $(\beta'_{i,I}, \beta'_{i,O})'$ in Equation (2), we can write the average return as $E[r_{i,t}] = \alpha^*_i + \beta^{*\prime}_{i,I}\lambda_I + \beta^{*\prime}_{i,O}\lambda_O = \alpha_i + \beta'_{i,I}\lambda_I$.

[3] For instance, suppose that fund i changes its allocation to the equity market linearly based on current economic conditions measured by the demeaned variable z_{t-1}. In this case, the market beta equals $\beta_{i,m,t-1} = \beta^*_{i,m,0} + \beta^*_{i,m,1} z_{t-1}$, and the correct benchmark is given by $r^B_{i,t} = \beta^{*\prime}_i f_t = [\beta^*_{i,m,0}, \beta^*_{i,m,1}][r_{m,t}, z_{t-1} r_{m,t}]'$, where $r_{m,t}$ is the excess market return, and $z_{t-1} r_{m,t}$ is the excess return of the dynamic strategy driven by the scaled factor $z_{t-1} r_{m,t}$ (Cochrane, 2005).

Noting that $\beta_{i,I} = \beta^*_{i,I} + \Psi'_{O,I}\beta^*_{i,O}$, we obtain:

$$\alpha_i = \alpha^*_i + \beta^{*\prime}_{i,O}[\lambda_O - \Psi_{O,I}\lambda_I] = \alpha^*_i + \beta^{*\prime}_{i,O}\alpha_O. \tag{4}$$

Equation (4) reveals that α_i is informative about the true alpha α^*_i. However, this information is noisy because α_i is also impacted by the omitted factor component $\beta^{*\prime}_{i,O}\alpha_O$.[4]

2.2.2. Comparison of Misspecified Models

To mitigate the impact of misspecification, we measure hedge fund performance across multiple models. This comparison analysis is important for several reasons. First, it describes how hedge fund performance varies across models. Therefore. it sheds light on the importance of choosing models that are significantly more complex than the CAPM – a choice commonly made in the hedge fund literature.[5] Second, it sharpens the estimation of hedge fund performance. Because existing models include different sets of factors, some are likely to do a better job at reducing the omitted factor component in Equation (4). Finally, this analysis determines the economic importance of the different factors. Focusing on the marginal contribution of each factor is useful to construct future models that are less prone to misspecification.

Our comparison analysis is based on the entire cross-sectional alpha distribution – in particular, its mean and variance. The mean is informative about the overall performance of the hedge fund industry, whereas the variance captures the potentially large performance dispersion across funds.

[4]If the factors are uncorrelated ($\Psi^k_{O,I} = 0$), Equation (4) becomes: $\alpha_i = \alpha^*_i + \beta^{*\prime}_{i,O}\lambda_O$, where the impact of each omitted factor is captured by its return premium – a quantity that does not depend on the specific factors $f_{I,t}$ included in the misspecified model (contrary to α_O). This assumption is largely consistent with the data because hedge funds factors tend to be weakly correlated (as shown in Table III).

[5]See Getmansky, Lee, and Lo (2015) and Agarwal, Mullally, and Naik (2015) for a review of hedge fund models that typically include a large number of factors across multiple asset classes.

For each misspecified model, we can use Equation (4) to write these two moments as:

$$E[\alpha_i] = E[\alpha_i^*] + E[\beta_{i,O}^*]'\alpha_O \,, \tag{5}$$

$$V[\alpha_i] = V[\alpha_i^*] + \alpha_O'\Sigma_{\beta_{i,O}^*}\alpha_O + 2\alpha_O' Cov[\beta_{i,O}^*, \alpha_i^*] \,, \tag{6}$$

where $E[\alpha_i^*]$ and $V[\alpha_i^*]$ are the cross-sectional mean and variance of the true alpha, $E[\beta_{i,O}^*]$ and $\Sigma_{\beta_{i,O}^*}$ are the cross-sectional mean vector and covariance matrix of the betas on the omitted factor, and $Cov[\beta_{i,O}^*, \alpha_i^*]$ denotes the vector of covariances between $\beta_{i,O}^*$ and α_i^*. Consistent with our discussion of Equation (2), we assume that the return premium associated with each omitted factor is positive (*i.e.*, $\alpha_O > 0$).

Equations (5) and (6) provide several insights. If hedge funds load positively on the factors f_t to boost their returns, we expect the vector $E[\beta_{i,O}^*]$ to be positive. In this case, using a misspecified model overestimates the true hedge fund performance (*i.e.*, $E[\alpha_i] > E[\alpha_i^*]$). A comparison analysis allows us to examine when $E[\alpha_i]$ seem implausibly large, and how it decreases when we increase the number of factors.

Contrary to the mean, the variance obtained with a misspecified model is not necessarily lower than the true variance. On the one hand, $V[\alpha_i]$ increases because α_i absorbs the cross-sectional variation in the fund beta associated with each omitted factor j ($\alpha_{j,O}^2 V[\beta_{i,j,O}^*] > 0$). On the other hand, $V[\alpha_i]$ could decrease if the fund beta on the omitted factor j is (i) negatively cross-correlated with the beta of another omitted factor j' ($\alpha_{j,O} Cov[\beta_{i,j,O}^*, \beta_{i,j',O}^*]\alpha_{j',O} < 0$), or (ii) negatively correlated with the true alpha ($\alpha_{j,O} Cov[\beta_{i,j,O}^*, \alpha_i^*] < 0$).[6]

[6]For instance, we would have a negative covariance between $\beta_{i,j,O}^*$ and α_i^* if some funds hide their lack of skill by loading aggressively on the factor j.

3. Methodology

3.1. Overview of the Estimation Approach

We now describe our new approach for estimating hedge fund performance across models. Our approach exhibits two main features. First, it explicitly allows each model to be misspecified. This feature is motivated by our previous analysis that any model is likely to omit some relevant factors that drive hedge fund returns. As we show below, accounting for model misspecification dramatically changes the statistical inference on performance evaluation.

Second, our approach provides a unified framework for estimating a large set of characteristics that determine the shape of the alpha distribution. These include: (i) the centered moments (*e.g.*, mean, variance), (ii) the proportion of funds with alphas below a given threshold a (*e.g.*, $a = 0$) inferred from the cumulative distribution function (cdf), and (iii) the quantile at a given percentile level u (*e.g.*, $u = 10\%$). For each estimated characteristic, we derive its asymptotic distribution as the numbers of funds n and return observations T grow large (simultaneous double asymptotics with n and $T \to \infty$). We can, therefore, conduct a proper statistical inference to formally evaluate and compare the performance obtained with different models.

3.2. Estimation of the Fund Alpha

We consider a set of K misspecified models. Each model k ($k = 1, ..., K$) includes the factors $f^k_{I,t}$, but omits the factors $f^k_{O,t}$ (with $f_t = (f^{k\prime}_{I,t}, f^{k\prime}_{O,t})'$). For each model k, we evaluate performance using as only inputs the estimated alphas of all funds in the population. To this end, we run the time-series regression for each fund i ($i = 1, ..., n$) as shown in Equation (3). The OLS vector of coefficients is given by

$$\hat{\gamma}_i = \hat{Q}^{-1}_{x,i} \frac{1}{T_i} \sum_t I_{i,t} x_t r_{i,t} \,, \tag{7}$$

where $I_{i,t}$ is an indicator variable equal to one if $r_{i,t}$ is observable (and zero otherwise), $T_i = \sum_t I_{i,t}$, $x_t = (1, f'_{I,t})'$, and $\hat{Q}_{x,i} = \frac{1}{T_i} \sum_t I_{i,t} x_t x'_t$. To lighten notation, we do not superscript $\hat{\gamma}_i$, $f_{I,t}$ and x_t by k.

The panel of hedge fund returns is unbalanced which implies that the sample size T_i can be very small for some funds. In this case, the inversion of $\hat{Q}_{x,i}$ is numerically unstable and yields unreliable estimates of $\hat{\gamma}_i$. To address this issue, we follow Barras, Gagliardini, and Scaillet (2020) and introduce a formal fund selection rule $\mathbf{1}_i^{\chi}$ equal to one if the following two conditions are met (and zero otherwise): $\mathbf{1}_i^{\chi} = \mathbf{1}\left\{CN_i \leq \chi_{1,T}, \tau_{i,T} \leq \chi_{2,T}\right\}$, where $CN_i = \sqrt{eig_{\max}\left(\hat{Q}_{x,i}\right)/eig_{\min}\left(\hat{Q}_{x,i}\right)}$ denotes the condition number of $\hat{Q}_{x,i}$, $\tau_{i,T} = T/T_i$, and $\chi_{1,T}$, $\chi_{2,T}$ denote the two threshold values.

The first condition $CN_i \leq \chi_{1,T}$ excludes funds for which the time series regression is poorly conditioned, *i.e.*, a large value of CN_i indicates multicollinearity problems and ill-conditioning (*e.g.*, Belsley, Kuh, and Welsch, 2004). The second condition $\tau_{i,T} \leq \chi_{2,T}$ excludes funds for which the sample size is too small. Both thresholds $\chi_{1,T}$ and $\chi_{2,T}$ increase with the sample size T – with more return observations, the fund coefficients are estimated with greater accuracy which allows for a less stringent selection rule. We denote the total number of funds that satisfy this selection rule by $n_{\chi} = \sum_{i=1}^{n} \mathbf{1}_i^{\chi}$.

3.3. *Statistical Inference under each Model*

3.3.1. *The Moments*

We begin our presentation with the estimation of the moments of the alpha distribution. We denote by M_j each centered moment ($j = 1, 2, ...$), and by $\hat{M}_j$ its corresponding estimator. For instance, we have for the mean and the standard deviation: $M_1 = E[\alpha_i]$, $M_2 = (E[\alpha_i^2] - E[\alpha_i]^2)^{1/2}$, and $\hat{M}_1 = \frac{1}{n_{\chi}} \sum_i \hat{\alpha}_i \mathbf{1}_i^{\chi}$, $\hat{M}_2 = \left(\frac{1}{n_{\chi}} \sum_i \mathbf{1}_i^{\chi} \hat{\alpha}_i^2 - \hat{M}_1^2\right)^{1/2}$. The following proposition derives the asympotic distribution of each estimated moment $\hat{M}_j$ under the misspecified model k.

Proposition 1. *As $n, T \to \infty$, such that $T/n = o(1)$,*

$$\sqrt{T}\left(\hat{M}_j - M_j\right) \Rightarrow N\left(0, V_{M_j}\right), \tag{8}$$

where $V_{M_j} = \left(\eta_{M_j}' \otimes E_1' Q_x^{-1}\right) \Omega_{ux} \left(\eta_{M_j} \otimes Q_x^{-1} E_1\right)$, and $\eta_{M_j} = E\left[\left(\frac{\partial M_j}{\partial E[g])}\right)' \frac{\partial g}{\partial \alpha_i} \beta_{i,O}^*\right]$, $E[g]$ is the vector of uncentered moments with $g = (\alpha_i, ..., \alpha_i^j)'$, $E_1 = (1, 0')'$, $Q_x = E[x_t x_t']$ and

$$\Omega_{ux} = \lim_{T\to\infty} V\left[\frac{1}{\sqrt{T}}\sum_t u_{O,t}\otimes x_t\right].$$

Proof. *See the Appendix.*

3.3.2. The Proportion and Quantile

Next, we turn to the analysis of the proportion and quantile. The proportion of funds with alphas below a is measured from the cumulative distribution function (cdf) and denoted by $P(a) = P[\alpha_i \leq a]$. The quantile at a given percentile u is given by the inverse function: $Q(u) = P^{-1}(u)$. Their estimators are given by $\hat{P}(a) = \frac{1}{n_\chi}\sum_i \mathbf{1}\{\hat{\alpha}_i \leq a\}\mathbf{1}_i^\chi$ and $\hat{Q}(u) = \hat{P}^{-1}(u)$. The following proposition derives the asympotic distributions of the estimated proportion $\hat{P}(a)$ and quantile $\hat{Q}(u)$ under the misspecified model k.

Proposition 2. *As $n, T \to \infty$, such that $T/n = o(1)$,*

$$\sqrt{T}\left(\hat{P}(a) - P(a)\right) \Rightarrow N\left(0, V_P(a)\right), \quad (9)$$

$$\sqrt{T}\left(\hat{Q}(u) - Q(u)\right) \Rightarrow N\left(0, V_Q(u)\right), \quad (10)$$

*where $V_P(a) = \left(\eta_P(a)'\otimes E_1'Q_x^{-1}\right)\Omega_{ux}\left(\eta_P(a)\otimes Q_x^{-1}E_1\right)$, $\eta_P(a) = E[\beta_{O,i}^*|\alpha_i = a]\phi(a)$, $\phi(a)$ is the alpha distribution (*i.e.*, the probability distribution function (pdf) evaluated at a), and $V_Q(u) = \frac{V_P(Q(u))}{\phi(Q(u))^2}$.*

Proof. *See the Appendix.*

3.3.3. Interpretation of the Results

Propositions 1 and 2 show that the estimated characteristics of the alpha distribution (moments, proportion, quantile) all share similar properties. They are asymptotically normally distributed, which facilitates the construction of confidence intervals. They are also consistent, *i.e.*, they converge towards the parameter values as n and T grow large. Put differently, we can infer the alpha distribution obtained with model k even though we do not observe the fund alphas themselves, but only their estimated values ($\hat{\alpha}_i$ instead of α_i). Finally, all estimated characteristics converge at a rate equal to the standard parametric rate $\sqrt{T}$. This last result is a priori surprising because the estimated characteristics are all computed as cross-sectional averages (*i.e.*, we sum across n, not across T).

These properties depart significantly from those derived by Barras, Gagliardini, and Scaillet (2020) for the correctly-specified case. First, the estimated characteristics have a smaller variance. Their convergence rate is equal to $\sqrt{n}$, which is much faster than $\sqrt{T}$ with a total population of several thousand funds. Second, the estimated characteristics must be adjusted for the error-in-variable (EIV) bias which has order $1/T$. This bias arises because we use the estimated alphas as inputs ($\hat{\alpha}_i$ instead of α_i). Strikingly, the EIV bias adjustment is unnecessary when the model is misspecified. Therefore, Propositions 1 and 2 provide a theoretical justification to the common practice of computing summary statistics based on estimated coefficients (*e.g.*, boxplots), but only if the model is misspecified.

These sharp difference arise from the properties of the residual term. The residuals $\varepsilon^*_{i,t}$ ($i = 1, ..., n$) in the correctly-specified case (Equation (2)) are weakly correlated because the common factors exhaust the cross-sectional dependence across hedge funds returns. In contrast, the residuals $\varepsilon_{i,t}$ ($i = 1, ..., n$) in the misspecified case (Equation (3)) are strongly correlated across funds because they include the omitted factors via the term $u_{O,t}$, *i.e.*, we have $\varepsilon_{i,t} = \varepsilon^*_{i,t} + \beta^{*\prime}_{O,i} u_{O,t}$. Therefore, the estimation error on the coefficients $\hat{\gamma}_i$ for each fund involves the time-series average $\bar{\varepsilon_i} = \bar{\varepsilon_i}^* + \beta^{*\prime}_{i,O} \bar{u_O}$, where $\bar{u_O}$ is of order $1/\sqrt{T}$ and does not vanish when we average across funds (even when n grows large). This term explains why all the estimated characteristics of the alpha distribution have a slower convergence rate equal to $\sqrt{T}$. In addition, they do not require the EIV bias adjustment because the variance term dwarfs the EIV bias in magnitude.

3.4. Formal Comparison across Models

3.4.1. The Moments

We now extend the previous analysis to formally compare the moments of the alpha distribution under two different models. To this end, we denote by ΔM_j the difference between the j^{th} centered moments obtained with models k and l, and by $\Delta \bar{M}_j$ the corresponding estimator, where

$\Delta M_j = M_j^k - M_j^l$ and $\Delta \hat{M}_j = \hat{M}_j^k - \hat{M}_j^l$.[7] The following proposition derives the asymptotic distribution of the estimated moment difference $\Delta \hat{M}_j$ under the misspecified models k and l.

Proposition 3. *As $n, T \to \infty$, such that $T/n = o(1)$,*

$$\sqrt{T}\left(\Delta \hat{M}_j - \Delta M_j\right) \Rightarrow N\left(0, V_{\Delta M_j}\right), \tag{11}$$

where $V_{\Delta M_j} = V_{M_j^k} + V_{M_j^l} - 2Cov[\hat{M}_j^k, \hat{M}_j^l]$, $V_{M_j^k}$, $V_{M_j^l}$ are given in Proposition 1, $Cov[\hat{M}_j^k, \hat{M}_j^l] = \left(\eta_{m_j^k{}'} \otimes E_1' Q_{x^k}^{-1}\right) \Omega_{ux}^{kl} \left(\eta_{m_j^l} \otimes Q_{x^l}^{-1} E_1\right)$, and $\Omega_{ux}^{kl} = \lim_{T\to\infty} Cov\left[\frac{1}{\sqrt{T}} \sum_t u_{O,t}^k \otimes x_t^k, \frac{1}{\sqrt{T}} \sum_t u_{O,t}^l \otimes x_t^l\right]$.
***Proof**. See the Appendix.*

3.4.2. The Proportion and Quantile

Repeating the above procedure for models k and l, we denote by $\Delta P(a) = P^k(a) - P^l(a)$ the difference between the proportions at the threshold a, and by $\Delta Q(u) = Q^k(u) - Q^l(u)$ the difference between the quantiles at the percentile u. We also denote by $\Delta \bar{P}(a)$ and $\Delta \bar{Q}(u)$ their corresponding estimators, where $\Delta \hat{P}(a) = \hat{P}^k(a) - \hat{P}^l(a)$ and $\Delta \hat{Q}(u) = \hat{Q}^k(u) - \hat{Q}^l(u)$.

The following proposition derives the asympotic distribution of the estimated proportion and quantile differences $\Delta \hat{P}(a)$ and $\Delta \hat{Q}(u)$ under the misspecified models k and l.

Proposition 4. *As $n, T \to \infty$, such that $T/n = o(1)$,*

$$\sqrt{T}\left(\Delta \hat{P}(a) - \Delta P(a)\right) \Rightarrow N\left(0, V_{\Delta P(a)}\right), \tag{12}$$

$$\sqrt{T}\left(\Delta \hat{Q}(u) - \Delta Q(u)\right) \Rightarrow N\left(0, V_{\Delta Q(u)}\right), \tag{13}$$

where $V_{\Delta P(a)} = V_{P^k(a)} + V_{P^l(a)} - 2Cov[\hat{P}^k(a), \hat{P}^l(a)]$, $V_{\Delta Q(u)} = V_{Q^k(u)} + V_{Q^l(u)} - 2Cov[\hat{Q}^k(u), \hat{Q}^l(u)]$, $V_{P^k(a)}$, $V_{P^l(a)}$, $V_{Q^k(u)}$, $V_{Q^l(u)}$ are given in Proposition 2. The two covariance terms are given by $Cov[\hat{P}^k(a), \hat{P}^l(a)] = \left(\eta_P^{k\prime}(a) \otimes E_1' Q_{x^k}^{-1}\right) \Omega_{ux}^{kl} \left(\eta_P^l(a) \otimes Q_{x^l}^{-1} E_1\right)$, and $Cov[\hat{Q}^k(u), \hat{Q}^l(u)] = Cov[\hat{P}^k(\hat{Q}^k(u)), \hat{P}^l(\hat{Q}^l(u)))]/(\phi^k(\hat{Q}^k(u))\phi^l(\hat{Q}^l(u)))$.
***Proof**. See the Appendix.*

[7] We assume in Proposition 3 that the two models are misspecified. If one model is correctly specified, the convergence rate of the estimated moment equals $\sqrt{n}$ (see Barras, Gagliardini, and Scaillet (2020)), which is much faster than the rate of $\sqrt{T}$ under the misspecified model. In this case, the asymptotic distribution of $\Delta \hat{M}_j$ is solely driven by the estimated moment under the misspecified model (*i.e.*, we can treat the estimated moment under the correctly-specified model as known).

3.4.3. Hypothesis Tests

From Proposition 3, we can formally test the null hypothesis that the j^{th} moments M_j^k and M_j^l under models k and j are equal:

$$H_0 : \Delta M_j = 0\,. \tag{14}$$

Similarly, we can use Proposition 4 to test the null hypothesis that the proportion or the quantile remains unchanged across the two models:

$$\begin{aligned} H_0 &: \Delta P(a) = 0\,, \\ H_0 &: \Delta Q(u) = 0\,. \end{aligned} \tag{15}$$

The testing procedure in Equations (14) and (15) is straightforward. The estimated differences in characteristics are all normally distributed, which allows for a simple computation of the rejection thresholds. Moreover, this procedure applies to the comparison of both nested and non-nested models. In contrast, Kan and Robotti (2011) and Kan, Robotti, and Shanken (2013) show that comparison tests of the pricing errors of misspecified models depend on whether they are nested or not. This difference arises because our asymptotic framework allows for n to grow large (instead of working with a fixed n). Second, we compare different quantities, i.e., our tests are based on the difference in the alpha distribution (instead of aggregate pricing errors such as the Hansen-Jagannathan distance and cross-sectional R^2).

3.5. Estimation of the Asymptotic Variance

To conduct statistical inference both within and across models, we need to estimate the asymptotic variance of the different estimators. The main difficulty is that each variance term in Propositions 1–4 depend on the omitted factors $u_{O,t}$ and their loadings $\beta^*_{i,O}$, which are not directly observable. To address this issue, we derive a consistent estimator of V based on the observed residuals of each model $\hat{\varepsilon}_{i,t} = r_{i,t} - x_t'\hat{\gamma}_i$ $(i = 1, ..., n)$.

To simplify the exposition, we consider the case where $\varepsilon_{i,t}$ is independent over time.[8] We consider the following generic expressions for (i) the variance of each estimated characteristic (*i.e.*, $\hat{M}_j, \hat{P}(a), \hat{Q}(u)$), and (ii) the variance of each estimated difference in characteristics between models k and l (*i.e.*, $\Delta\hat{M}_j, \Delta\hat{P}(a), \Delta\hat{Q}(u)$):

$$\hat{V} = \frac{1}{n^2 T} \sum_i \sum_j \sum_t \mathbf{1}_i^{\chi} \tau_{i,T} I_{i,t} \mathbf{1}_j^{\chi} \tau_{j,T} I_{j,t} \hat{a}_{i,t} \hat{a}'_{j,t}\,, \tag{16}$$

where the term $\hat{a}_{i,t}$ depend on each estimator. For instance, we have $\hat{a}_{i,t} = E_1' \hat{Q}_x^{-1}$ for the cross-sectional mean M_1. The appendix reports the expressions of $\hat{a}_{i,t}$ for the other characteristics, and shows that $\hat{V}$ and $\hat{V}_{\Delta}$ are consistent estimators of V and V_{Δ} as n and T grow large.

4. Data Description

4.1. Hedge Fund Database

We evaluate hedge fund performance using the monthly net-of-fee USD returns of individual funds over the period 1994-2016 (276 observations). We take several steps to mitigate the various sources of bias in the hedge fund databases. First, we create an exhaustive universe of funds by aggregating five different data providers (BarclayHedge, Eurekahedge, HFR, Morningstar, and TASS). Because under-performing funds typically report to only one provider, combining databases offers a better representation of these funds and thus reduces the upward selection bias in individual databases (Joenväärä, Kauppila, Kosowski, and Tolonen, 2019). Second, we address survivorship bias by including the dead funds from the graveyard hedge fund databases available from January 1994 onward. Third, we follow previous studies and delete the first 12 months of data to mitigate the backfill bias when funds start reporting to databases.[9] The appendix provides

[8]This assumption holds if the residual $\varepsilon^*_{i,t}$ and the omitted factors $f_{O,t}$ are independent over time. When this is not the case, we simply need to modify the variance estimator by including weighted cross-terms at different dates (Newey and West, 1987).

[9]A more stringent approach examined in the appendix is to eliminate all the return observations before the fund listing date to the database. As noted by Fung and Hsieh (2009), this approach potentially discards important infor-

more detail on the construction of the hedge fund dataset.

We evaluate the performance of several hedge fund strategies across three broad hedge fund categories: equity, macro, and arbitrage. This classification facilitates the identification of relevant factors within each category.[10] The first category (equity) includes long-short and market neutral funds. The second category (macro) includes global macro funds and managed futures funds/commodity trading advisors (for simplicity, both are referred to as CTAs). Finally, the third category (arbitrage) includes relative value and event-driven funds. The mapping of strategies across the different databases builds on the recent paper by Joenväärä, Kauppila, Kosowski, and Tolonen (2019) and is described in the appendix.

Table I reports summary statistics for the consolidated hedge fund database. For each category/style, we construct the excess return of an equally-weighted portfolio that includes all existing funds at the start of each month. We then report the average number of funds per month, the mean, standard deviation (both annualized), skewness, kurtosis, and quantiles at 10% and 90%. Overall, the results are in line with those documented by Getmansky, Lee, and Lo (2015) over a similar period (1996–2014). For instance, they find that the mean-volatility pair equals 4.7%-3.3% for market neutral funds and 6.8%-5.9% for event-driven funds, versus 4.1%-3.3% and 6.7%-6.2% in Table I. Consistent with intuition, we find that long-short equity and CTA funds exhibit higher levels of volatility as they typically take more directional positions.

To conduct our fund-level performance analysis, we apply the two selection rules described in Section 3.2. First, we fix the minimum number of return observations equal to 36 ($\tau_{i,T} \leq 276/36$) to keep a large number of funds. Second, we follow Barras, Gagliardini, and Scaillet (2020) and impose that the condition number of the matrix of regressors $\hat{Q}_{x,i}$ is below 15 ($CN_i \leq 15$).

mation about the fund performance by eliminating all the early years of returns (in some cases, more than 5 years) – a period during which performance is typically quite strong (Aggarwal and Jorion, 2010). In addition, the listing date is not provided by all databases.

[10] For this reason, we initially exclude multi-strategy funds and funds of funds. These two categories are discussed later in Section 5.3.

Combining these two rules, we obtain a total number of 8,665 funds over our sample period.[11]

[Insert Table I about here.]

4.2. Hedge Fund Factors

Building on previous work, we collect the return time-series of 28 economically-motivated factors. These factors can be easily interpreted as they capture the excess return of mechanical strategies that hedge funds potentially follow. As such, they depart from purely statistical hedge fund factors extracted from a PCA analysis (*e.g.*, Fung and Hsieh, 2001; Billio, Getmansky, Lo, and Pelizzon, 2012). Combining these factors, we then evaluate hedge fund performance across multiple models.

Table II provides the list of the 28 hedge fund factors, which are discussed in more detail in Section 5. Group 1 includes the set of US equity factors which include the market, size, value, momentum, investment, and profitability factors. It also includes the liquidity factor, and the Betting-Against-Beta (BAB) factor which captures the impact of leverage constraints. Group 2 contains strategies across the other asset classes. It includes the term and default factors for US bonds, the excess return of commodity and currency indices, and the two global value and momentum factors applied to international equities, bonds, commodities, and currencies. Group 3 contains a set of option-based strategies. It includes the correlation and variance factors inferred from options on the S&P 500 and its constituents, and the excess returns of three look-back option straddles on bonds, commodities, and currencies.[12] Group 4 includes the set of carry strategies across international equities, bonds (level, slope), commodities, and currencies. Group 5 includes the set of time-series (TS) momentum strategies across international equities, bonds, commodities,

[11]In our sample, the second criterion is redundant because the final population size is determined by the minimum number of return observations.

[12]Contrary to the other factors, the option-based strategies are expected to deliver negative return premia because they perform well in bad times when realized variance/correlation is high. To maintain consistency with the other factors, we therefore multiply their returns by -1 such that the investor takes a short position in these option-based strategies.

and currencies. The appendix provides a detailed description of the construction and data source for each factor.

Table II reports the summary statistics for the excess return of each factor. Consistent with previous studies, we find that the trading strategies associated with the different factors all deliver positive average returns (*i.e.*, $\lambda > 0$). Therefore, any fund that loads positively on these factors earns a positive premium. We also examine the correlation across factors. To this end, we compute the correlations (in absolute value) for all factor pairs, and take an average both within and across the five groups. Table III shows that the factors are weakly correlated, even within specific groups (*e.g.*, the average correlation equals 0.19 across time-series momentum factors). Unreported results further show that only four of the 378 pairwise correlations are above 0.6 (in absolute value). Overall, these results imply that the factors capture distinct hedge fund trading strategies.

[Insert Tables II and III about here.]

5. Empirical Results

5.1. Performance Analysis with Standard Models

We begin our performance analysis by examining a set of standard models from the literature on asset pricing and performance evaluation. These models are convenient for the analysis of hedge funds because they are designed as "omnibus" models that include multiple factors across asset classes. Therefore, they can, in principle, explain the returns of multiple hedge fund categories. In addition to the CAPM which serves as a natural reference point, we examine the following models:

1. 3-Factor Model: This model proposed by Fama and French (1993) includes the market, size, and value factors;
2. Asness-Moskowitz-Pedersen (AMP) Model: This three-factor model proposed by Asness, Moskowitz, and Pedersen (2013) includes the market return and the two global value and momentum factors (value and momentum everywhere);

3. 4-Factor Model: This model proposed by Carhart (1997) adds the momentum factor to the 3-Factor model;
4. 5-Factor Model: This model propposed by Fama and French (2015) adds the investment and profitability factors to the 3-Factor model;
5. Hasanhodzic-Lo Model: This six-factor model proposed by Hasanhodzic and Lo (2007) includes the market and size factors, the term and default bond factors, and the excess return of the commodity and currency indices;
6. Fung-Hsieh Model: This seven-factor model proposed by Fung and Hsieh (2004) includes the market and size factors, the term and default bond factors, and the excess returns of the lookback option straddles on bonds, commodities, and currencies.

For each model, we apply the approach outlined in Section 3 to estimate several characteristics of the cross-sectional alpha distribution. We compute the annualized mean and standard deviation ($\hat{M}_1$ and $\hat{M}_2$), the proportions of funds with negative and positive alphas ($\hat{P}(0)$ and $1 - \hat{P}(0)$), and the annualized quantiles at 10% and 90% ($\hat{Q}(0.1)$ and $\hat{Q}(0.9)$).

The main insight from Table IV is that all the models yield the same performance evaluation. The average alpha, which equals 2.62% per year with the CAPM, barely changes as we include more factors. For instance, it is equal to 2.25% and 2.79% per year with the 3-factor and Fung-Hsieh models. This result resonates with that of Getmansky, Lee, and Lo (2015) who show that a simplified version of the Fung-Hsieh model leaves the average alpha largely unchanged. Beyond the average, we find that the entire alpha distribution has the same dispersion and tail properties across models – that is, the standard deviation, proportions, and quantiles all remain largely unchanged.[13]

[Insert Table IV about here.]

[13]In unreported results, we find that the strong similarity across models extends to the alpha of each individual fund. For instance, the fund-level correlation between the CAPM alpha and the Fung-Hsieh alpha is as large as 0.94.

These results are confirmed by our formal comparison tests. For each characteristic (average, standard deviation, proportion, quantile), we test the null hypothesis that the estimated difference between model k and model l is equal to zero. Each row in Table V reports the estimated differences for a given model k. Therefore, a negative value implies that model k has a lower characteristic than model l. Out of the 210 comparisons, we find that only 20 of them are statistically significant at the 10% level. This number is negligible – even if all the differences were equal to zero, we would expect to find 21 rejections simply by luck (see Barras, Scaillet, and Wermers, 2010).[14]

Taken at face value, the empirical evidence implies that the performance of the hedge fund industry is economically large. More than 65% of the funds deliver a positive alpha – a finding that resonates with that of Chen, Cliff, and Zhao (2017) who find that 91% of the funds have an alpha equal or superior to zero. Furthermore, some of these positive-alpha funds deliver a stellar performance to investors – as shown by the 90%-quantile across models, the best performers typically deliver annual alphas above 11% per year.

[Insert Table V about here.]

Alternatively, the strong performance under the standard models could simply be due to misspecification. To examine this issue, we first compute the adjusted R^2 from the time-series regression in Equation (3). A low R^2 is a sign of misspecification because it suggests the presence of omitted factors that drive hedge fund returns.[15] Second, we use the diagnostic criterion of Gagliardini, Ossola, and Scaillet (2019, GOS) to detect misspecification. When a model is misspecified, the fund residuals are strongly correlated (see Section 3.3). In this case, the GOS diagnostic cri-

[14]We also find that performance remains largely unchanged for each hedge fund category (equity, macro, arbitrage). For instance, the largest difference for the mean and standard deviation is a mere 0.57% and 0.31% per year among equity funds (see the appendix).

[15]Using the Fung-Hsieh model, Bollen (2013) notes that many hedge funds have a R^2 close to zero. However, their residual volatility cannot be diversified away which suggests that they all depend on the same omitted factors.

terion is positive with probability one when n and T grow large.[16] The evidence in Table IV (Panel A) strongly suggests that the standard models are misspecified. We find that the average R^2 ranges between 20% and 30%, leaving plenty of room for omitted factors. In addition, the GOS criterion is also always positive which implies that the residuals exhibit a strong factor structure.

In the next section, we examine whether using alternative hedge fund factors potentially reduces the impact of misspecification. To this end, we study each hedge fund category separately (equity, macro, and arbitrage). This approach allows us to identify a set of plausible economic factors that potentially drive the returns within each category. In addition, it mitigates data-mining concerns that arise if we were to evaluate a very large number of randomly formed models.

5.2. An Analysis of Alternative Hedge Fund Factors

5.2.1. Equity Funds

We begin our analysis with the equity category (long-short and market neutral funds). Equity funds rely on discretionary or quantitative analysis to buy undervalued stocks and sell short overvalued stocks. As a result, their returns are potentially correlated with several trading strategies.

1. Correlation and variance. Equity funds can be exposed to correlation and variance risks. As discussed by Buraschi, Kosowski, and Trojani (2014), unexpected increases in correlation and variance limits the funds' ability to balance risk between their long and short positions, and typically occur in crisis times when prime brokers tighten their funding conditions.
2. Market liquidity. Equity funds may be exposed to marketwide liquidity risk. This exposure arises because equity funds commonly buy small-cap stocks and accommodate selling pressure in the market (*e.g.* Pedersen, 2015, ch.3).
3. Betting-against-beta (BAB). Traditional investors face leverage constraints and thus shy away from low-risk stocks. Equity funds can take advantage of their additional leverage capacity to buy these stocks – a strategy captured by the BAB factor.

[16]The GOS criterion is described in more detail in the appendix and is applied by Chaieb, Langlois, and Scaillet (2018) in the context of individual international stock returns.

4. Equity carry. Equity funds invest across multiple international equity markets. To determine their overall allocation, they may follow a carry strategy which invests in equity markets with high dividend yields.
5. Equity TS momentum. To determine their overall allocation, equity funds may also follow a TS momentum strategy which favors markets with high past returns relative to their own average.

We construct an extended CAPM that includes the market return and the following factors: the correlation and variance factors of Buraschi, Kosowski, and Trojani (2014), the traded liquidity factor of Pástor and Stambaugh (2003), the BAB factor of Frazzini and Pedersen (2014), the equity carry factor of Koijen, Moskowitz, Pedersen, and Vrugt (2018), and the equity TS momentum factor of Moskowitz, Ooi, and Pedersen (2012).

Table VI (Panel A) measures the overall impact of the factors on the performance of equity funds. A first look at the results suggests that the extended model remains misspecified. On average, the R^2 is still relatively low (33.53%), and the GOS criterion remains positive (*i.e.*, the fund residuals are strongly correlated). However, it achieves a sizeable reduction in the overall performance of equity funds. The average alpha is a mere 0.36% per year (versus 2.06% for the CAPM), and the proportion of positive-alpha funds is equal to 52.86% (versus 66.55% for the CAPM).

An important question is whether the overall impact of the alternative factors is genuine. Because misspecification introduces estimation noise, the estimated differences may not be statistically significant even though they are economically large. Panel A shows that this is not the case – the difference between the average alphas (-1.70%) and the proportion estimates (-13.70%) are both significant at the 1% level.

The alternative factors also change the dispersion of the fund alphas. Whereas we might expect the standard deviation under the extended CAPM to decrease as we remove the variation due to the omitted factors, it actually increases from 8.19% to 10.09% per year. The extended model also lowers the performance of the worst funds. The bottom 10% of the funds deliver alphas below -9.13% per year (versus -6.47% under the CAPM).

Next, we examine the economic importance of the each factor in isolation. To this end, we measure the return premium $rp_{i,j}$ associated with each factor as its contribution to the difference between the fund alphas under the CAPM and the alternative model. From Equation (4), we can write this difference as:

$$\alpha_i^{\text{CAPM}} - \alpha_i^{\text{COMB}} = \sum_j^6 rp_{i,j} = \sum_j^6 \beta_{i,j}^{\text{COMB}} \alpha_j^{\text{CAPM}}, \tag{17}$$

where the subscript j denotes one of the factors included in the combined model, $\beta_{i,j}^{\text{COMB}}$ is the fund beta, and α_j^{CAPM} denotes the CAPM alpha of the factor. After computing $rp_{i,j}$ for each fund, we can infer its cross-sectional distribution for each factor j ($j = 1, ..., 6$). Table VI (Panel B) reveals several insights. First, the majority of equity funds have a positive beta on each factor (57.09% on average), and earn positive return premia by doing so (0.28% per year on average). This finding supports the view that hedge funds load on non-conventional risk factors to boost their average returns. Second, we find that the variance and TS momentum factors are the main drivers of the average returns of equity funds – they explain 58% of the average difference between α_i^{CAPM} and α_i^{COMB} (0.99%/1.70%). Third, we observe a large heterogenity in the funds' exposure to the correlation, variance, and BAB factors. For instance, the BAB factor contributes little to the mean return of equity funds (0.04% per year). However, 10% of the funds earn more than 3.17% per year by leveraging their positions on low-risk stocks.

Looking at the fund-level correlation between return premia, we find little evidence that funds take correlated positions across factors – on average, the correlation between $rp_{i,j}$ and $rp_{i,j'}$ ($j \neq j'$) is close to zero (-0.04). Therefore, equity funds load on the alternative factors but do not exploit the diversification benefits that arise from their low correlation (as shown in Table III). On the contrary, the correlation between $rp_{i,j}$ and α_i^{COMB} is equal to -0.19 on average. This negative correlation implies that poorly performing funds tend to load more aggressively on the different trading strategies.

[Insert Table VI about here.]

In the appendix, we repeat the analysis for each investment style (long-short and market neutral funds). We find that the alternative factors have a stronger impact on long-short funds – the average difference in alphas between the two models is equal to 1.77% per year. In contrast, this difference is a mere 1.22% for market neutral funds. This finding is consistent with the intuition that market neutral funds have a limited exposure to systematic risk. Another striking difference between the two subgroups is the role played by the BAB factor. On average, it is the main contributor to the returns of market neutral funds (0.48% per year). Leveraging on low-beta stocks allows these funds to boost their returns while maintaining a neutral exposure to the aggregate market.

5.2.2. Macro Funds

We now turn to the analysis of the macro category (global macro and CTA funds). Contrary to equity funds, macro funds invest in multiple asset classes, and take directional bets using broad economic and financial indicators (*e.g.*, GDP growth, inflation). These two differences call for a generalization of carry and TS momentum to multiple asset classes.

1. Carry. Macro funds generally favor assets that have a positive carry within each asset class (Pedersen, 2015, ch.11) – by definition, such assets earn a positive income even if their price do not change over time. As shown by Koijen, Moskowitz, Pedersen, and Vrugt (2018), the concept of carry can be applied uniformly across equities, bonds (level), portfolios of long-term minus short-term bonds (slope), commodities, and currencies.
2. TS momentum. Macro funds also exploit short-term trends in asset prices caused by behavioral biases, frictions, or slow moving capital (Pedersen, 2015, ch.12). Therefore, their returns could be explained by mechanical times-series momentum strategies which invest in assets with high past returns across equity, bond, currency, and commodity markets.

We construct an extended version of the CAPM that includes five carry and four TS momentum strategies. We use the carry factors of Koijen, Moskowitz, Pedersen, and Vrugt (2018) for equities, bonds (level and slope), commodities, and currencies, and the TS momentum factors of Moskowitz, Ooi, and Pedersen (2012) for equities, bonds, commodities, and currencies.

The impact of these factors on the performance of macro funds is large. Table VII (Panel A) shows that the average CAPM alpha equals 3.32% per year with a proportion of positive-alpha funds close to 70%. Adding carry and TS momentum, the average alpha turns negative (-0.56%), and only a minority of funds exhibit positive alphas (45.33%). Our formal comparison analysis reveals that the above differences are not only economically large, but statistically significant at the 1% level. The results also show that this reduction in performance come with a sizeable increase in explanatory power (the average R^2 increases from 8.45% to 20.36%).

The alternative factors also have a strong impact on the left and right tails of the alpha distribution. Under the CAPM, the best performing funds deliver alphas above 13.75% per year. However, this seemingly stellar performance is partly driven by carry and TS momentum – accounting for these strategies, the 90%-quantile is only equal to 10.62%. Similarly, we observe a sharp drop in the 10%-quantile from -7.44% to -12.42%.

Except for one case (currency carry), Table VII (Panel B) shows that the majority of macro funds are positively exposed to each alternative factor an earn a return premium of 0.43% per year on average. We also see that TS momentum is more important than carry in explaining the difference between the extended model and the CAPM – they explain 73% of the gap in average alpha (2.87%/3.92%), versus 27% for carry strategies (1.11%/3.92%).

For carry, the bond strategies (level and slope) are the main contributors to the individual fund returns. They produce both the highest average return premia – a combined 0.80% per year – and the highest standard deviation. Turning to the TS momentum, the two most important strategies are fixed income and currency – their combined return premium reaches 1.88% per year on average. We also observe a strong dispersion in the funds' exposure to the fixed income strategy. For instance, 10% of the funds earn a premium above 5.36% by exploiting trends in the bond market. Similar to equity funds, we also find that the return premia are (i) weakly correlated across factors, and (ii) negatively correlated with the alpha.

[Insert Table VII about here.]

In the appendix, we also examine the importance of the alternative factors for each investment style (global macro and CTA funds). In both subgroups, we observe a sharp reduction in performance relative to the CAPM. For instance, the average alpha respectively decreases by 3.03% per year for global macro funds, and by 4.43% for CTA funds. Interestingly, the relative importance of carry and TS momentum varies across the two subgroups. For global macro funds, the combined return premium of the carry strategies is equal to 1.13% per year, which is similar that of the TS momentum strategies (1.89%). On the contrary, CTA funds primarily focus on TS momentum – the combined return premium reaches 3.61%, which explains 82% of the difference between the average alphas between the two models (3.61%/4.43%). This finding resonates with the analysis of Pedersen (2015, ch.12) who shows that CTA fund indices deliver negative alphas once after controlling for TS momentum.

5.2.3. Arbitrage Funds

We finally examine the arbitrage category (relative value and event-driven). Arbitrage funds implement convergence trades by identifying similar securities that trade at different prices. Whereas relative value funds exploit price discrepancies in the debt market (*e.g.*, fixed income, convertible bond arbitrage), event-driven funds focus on corporate events such as mergers and acquisitions. As a result, arbitrage funds may follow several trading strategies.

1. Correlation and variance. Similar to the equity category, arbitrage funds take correlation and variance risks through their hedging strategies. In addition, several fixed-income funds (*e.g.*, mortgage and volatility arbitrage) follow option-based strategies which are sensitive to unexpected changes in variance.

2. Market liquidity. Arbitrage funds are potentially exposed to liquidity risk. This exposure arises when they take illiquid positions in the convertible bond market, or when they absorb the selling pressure after merger announcements (see Pedersen, 2015, ch.15 and 16).
3. Bond carry. Similar to the macro funds, arbitrage funds may also implement carry strategies. This is particularly the case for fixed-income funds when they search for high expected returns across bonds (Pedersen, 2015, ch.14)

We capture these strategies using an extended version of the CAPM that includes the following factors: the correlation and variance factors of Buraschi, Kosowski, and Trojani (2014), the traded liquidity factor of Pástor and Stambaugh (2003), and the carry factors of Koijen, Moskowitz, Pedersen, and Vrugt (2018) applied to bonds (level and slope).

Table VIII (Panel A) shows that the alternative factors produce a lower performance among arbitrage funds. However, their impact is lower than in the other categories. The difference between the average alphas is equal to -1.41% (versus -1.70% and -3.88% for equity and macro funds). Similarly, the proportion of positive-alpha funds decreases moderately from 71.68% to 62.28%. Overall, these results highlight the challenge of capturing the returns of arbitrage funds as they follow a large number of investment strategies with varying levels of complexity (see Duarte, Longstaff, and Yu, 2006).

Panel B shows that the majority of the funds load positively on each single factor (the average fund proportion equals 59.25%). We find that the variance factor produces the highest return premium (0.69% per year on average). This finding is consistent with the importance of option-based for arbitrage funds. We also see larger degree of homogeneity in the funds' exposures to the alternative factors. The average standard deviation in the return premium equals 2.30% per year – a level lower than the one observed for equity funds (3.57%) and macro funds (2.72%).

[Insert Table VIII about here.]

In the appendix, we further examine the impact of the alternative factors on each investment style (relative value and event-driven). We observe a similar decrease in performance in both subgroups. To illustrate, the average alpha decreases from 2.45% to 0.90% per year for relative value funds, and from 3.50% to 2.37% for event-driven funds. The results show that the bond carry strategies are more important for relative value funds – the combined return premium equals 0.93% on average. This is consistent with the greater activity of these funds in the fixed-income market. We also find that event-driven funds are more exposed to liquidity risk, possibly because they provide liquidity following merger announcements.

5.3. A New Model for Evaluating Hedge Fund Performance

Our analysis so far is useful for two reasons. First, it provides a rationale for using the set of alternative factors proposed in the recent literature – that is, it explains why each investment category might be more sensitive to particular factors. Second, it uncovers some commonality across the different categories. For instance, equity and arbitrage funds are exposed to correlation, variance, and liquidity risks, while all funds follow different types of carry strategies. This commonality suggests that a simple encompassing model could mitigate the impact of misspecification and improve the evaluation of hedge fund performance.

To address this issue, we propose a new model that includes seven factors: the market return, the correlation and variance factors of Buraschi, Kosowski, and Trojani (2014), the traded liquidity factor of Pástor and Stambaugh (2003), the BAB factor of Frazzini and Pedersen (2014), and the two global factors of Koijen, Moskowitz, Pedersen, and Vrugt (2018) and Moskowitz, Ooi, and Pedersen (2012) which capture the returns of carry and TS momentum across all asset classes (equity, bonds, commodities and currencies). We then evaluate hedge fund performance with this new model and compare it with four standard models examined in Table X: (i) the CAPM, (ii) the 4-factor model, (iii) the 5-factor model, and (iv) the Fung-Hsieh model.

The new model produces a more conservative evaluation of hedge fund performance. Table IX (Panel A) shows that the average alpha for the entire fund population is close to zero (-0.07% per year). In addition, we find that only 51.85% of the funds produce positive alphas. These results stand in sharp contrast with those obtained with the standard models. For one, the differences between the average alphas range between -2.24% (4-factor) and -2.86% (Fung-Hsieh) per year and are all statistically significant at the 1% level. We also find that the new model lowers performance in all three investment categories (Panels B to D). This reduction is particularly strong among equity and macro funds, where the average alpha turns negative and the majority of the funds deliver negative alphas to their investors.

Another insight from Table IX is the large heterogeneity in hedge fund performance. Even after accounting for several factors that drive the average returns of hedge funds, the standard deviation of the alpha distribution remains large at 11.54% per year. This result suggests that investors can collect huge rewards if they are able to locate the best funds in the right tail of the distribution. At the same time, the large dispersion in fund alphas is mostly driven by the left tail. Under the new model, the 10%-quantile is equal to -11.23% per year. Therefore, some hedge funds vastly overcharge their investors relative to the value they are able to generate. Interestingly, the 10%-quantile is more than 4% higher (in absolute value) under the standard models. The reason is that poorly performing funds load more aggressively on the alternative factors. Therefore, the negative alphas of poorly performing funds are partly hidden because they are offset by the positive premia associated with the omitted factors.

[Insert Table IX about here.]

Finally, we conduct a sensitivity analysis to determine whether the reduction in performance documented in Table IX holds in other settings. First, we examine two additional investment categories – multi-strategy funds and funds of funds. Table X (Panels A and B) confirms our previous findings. In particular, we find that the average alphas among funds of funds is equal to -3.48% per year, and only 24.75% of them deliver positive alphas to their investors. Second, we divide the sample period into two subperiods of 138 monthly observations each. Over the two subperiods (Panels C and D), the new model achieves a strong reduction in performance relative to the standard models.

[Insert Table X about here.]

6. Conclusion

Measuring the performance of hedge funds is challenging because they follow a large number of strategies. As a result, any model used for benchmarking performance is likely to be misspecified. In this context, comparing multiple models is essential to (i) describe their relative differences, (ii) sharpen the evaluation of performance, and (iii) assess the relative importance of the different factors.

In this paper, we develop a novel approach to perform such comparisons. Our approach provides an estimation of the entire alpha distribution obtained with any misspecified model. It is simple, informative, and allows for formal comparison tests. It is simple because it uses as only inputs the estimated fund alphas. It is informative because it captures the large heterogeneity in performance across funds. Finally, it allows for formal comparison tests derived from a full-fledged asymptotic theory.

The empirical results reveal that the standard models all produce the same strong performance, possibly because they omit relevant factors. Motivated by these findings, we examine a set of alternative factors proposed in recent work, including the correlation, variance, carry, and time-series momentum strategies. Our analysis explains why these factors are likely to drive the returns of hedge funds across different investment categories. It also shows that a simple model formed with these factors achieves a sizeable reduction in hedge fund performance.

Overall, our results suggest that the average hedge fund returns are largely explained by a set of mechanical strategies. However, all the models examined in this paper remain misspecified. Our estimation approach can therefore be used in future work for the examination of a larger set of factors. As the number of factors increases, it can also shed light on the importance of developing models targeted at specific hedge fund categories.

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TABLE I. Summary Statistics for the Equal-Weighted Portfolio of Funds

This table reports, for each investment category, the average number of funds per month, the average and volatility excess return (annualized), the skewness and kurtosis, and the 10th and 90th percentiles.

	Number of Funds	Moments				Quantiles	
		Mean(Ann.)	Std(Ann.)	Skewness	Kurtosis	10%	90%
All Funds	3,268	5.85	5.93	-0.27	4.05	-1.63	2.50
Equity	1,450	7.02	8.76	-0.44	4.90	-2.42	3.47
Long-Short	1,279	7.39	9.58	-0.42	4.90	-2.64	3.71
Market Neutral	171	4.09	3.33	-0.42	5.40	-0.67	1.54
Macro	924	4.77	6.37	0.49	3.45	-1.74	2.63
Global Macro	358	5.02	5.61	0.27	3.23	-1.63	2.43
CTA/Managed Futures	566	4.72	7.17	0.57	3.60	-1.97	3.03
Arbitrage	895	5.84	5.19	-1.96	13.55	-1.11	1.95
Relative Value	577	5.23	4.71	-2.30	17.90	-0.95	1.66
Event-Driven	317	6.73	6.21	-1.49	8.96	-1.42	2.42

TABLE II. Summary Statistics for the Factor Excess Returns

This table reports the average and volatility excess return (annualized), the skewness and kurtosis, and the 10th and 90th percentiles, of the various factors used in our study.

Panel A: US Equity

	Moments				Quantiles	
	Mean(Ann.)	Std(Ann.)	Skewness	Kurtosis	10%(Ann.)	90%(Ann.)
Market Index	7.56	15.13	-0.71	4.17	-5.11	6.00
Size	2.19	10.97	0.46	7.85	-3.56	3.65
Value	2.91	10.70	0.14	5.57	-2.95	3.62
Momentum	3.35	7.37	0.64	5.45	-1.85	2.98
Investment	4.15	9.70	-0.43	12.10	-2.04	3.21
Profitability	4.99	17.63	-1.49	13.26	-5.14	5.39
Liquidity	6.31	12.43	-0.13	4.11	-3.84	4.98
Betting Against Beta	8.58	13.52	-0.52	5.59	-3.56	4.73

Panel B: Other Asset Classes

	Moments				Quantiles	
	Mean(Ann.)	Std(Ann.)	Skewness	Kurtosis	10%(Ann.)	90%(Ann.)
US Bond Term	-0.14	0.78	-0.18	4.68	-0.27	0.27
US Bond Default	0.02	0.64	1.22	19.18	-0.15	0.17
Commodity Index	0.59	21.81	-0.34	4.19	-7.60	7.51
US Dollar Index	0.60	5.76	-0.42	4.80	-1.96	2.07
Value Everywhere	2.33	6.22	-0.70	13.40	-1.54	1.79
Momentum Everywhere	3.81	7.82	-0.32	5.33	-2.31	2.74

Panel C: Option Strategies

	Moments				Quantiles	
	Mean(Ann.)	Std(Ann.)	Skewness	Kurtosis	10%(Ann.)	90%(Ann.)
Equity Correlation	82.14	50.73	-2.40	17.70	-5.29	19.47
Equity Variance	1.19	1.31	-7.25	82.05	-0.05	0.34
Bond Straddle	20.09	52.77	-1.31	5.24	-18.99	17.73
Commodity Straddle	6.56	49.48	-1.06	4.53	-20.02	15.98
Currency Straddle	10.24	67.47	-1.36	5.51	-23.31	20.30

Panel D: Carry Strategies

	Moments				Quantiles	
	Mean(Ann.)	Std(Ann.)	Skewness	Kurtosis	10%(Ann.)	90%(Ann.)
Equity Carry	8.21	9.41	0.50	6.03	-2.27	4.01
Bond Carry - Level	3.48	4.44	-0.30	4.61	-1.20	1.85
Bond Carry - Slope	0.42	0.45	1.15	9.43	-0.11	0.18
Commodity Carry	9.88	17.19	0.18	3.49	-5.43	7.18
Currency Carry	4.75	7.36	-0.67	4.76	-2.49	2.72

Panel E: Time-Series Momentum Strategies

	Moments				Quantiles	
	Mean(Ann.)	Std(Ann.)	Skewness	Kurtosis	10%(Ann.)	90%(Ann.)
Equity TS Momentum	18.99	26.88	0.12	3.17	-8.37	11.80
Bond TS Momentum	17.72	28.32	0.10	4.24	-8.00	10.72
Commodity TS Momentum	10.36	15.32	-0.26	4.66	-4.29	6.22
Currency TS Momentum	11.63	17.94	0.38	5.23	-4.80	6.84

TABLE III. Pairwise Correlation between the Factor Excess Returns

This table reports the average pairwise correlations (in absolute value) in the universe of factors.

	US Equity	Other Asset Classes	Options	Carry	TS Momentum
US Equity	0.23	0.13	0.10	0.05	0.11
Other Asset Classes		0.20	0.15	0.10	0.20
Options			0.25	0.04	0.14
Carry				0.09	0.08
TS Momentum					0.19

TABLE IV. Hedge Fund Performance under the Standard Models

This table reports summary statistics for the cross-sectional distribution of the hedge funds alphas obtained with the standard models. Summary statistics are the average and the standard deviation of alphas, the proportions of negative and positive alphas, and the 10th and 90th percentiles of the alphas. We also report the average R^2 and the GOS diagnostic value.

	Moments		Proportions		Quantiles		Specif. Stats	
	Mean(Ann.)	Std(Ann.)	Negative	Positive	10%(Ann.)	90%(Ann.)	Avg.R^2	GOS
CAPM	2.62 (0.77)	9.19 (0.56)	31.66 (3.87)	68.34 (3.87)	-6.44 (1.37)	11.08 (1.37)	18.85	2.92
3-Factor	2.25 (0.72)	9.13 (0.49)	33.63 (3.78)	66.37 (3.78)	-7.03 (1.11)	10.72 (1.11)	21.77	2.60
AMP	2.25 (0.76)	9.30 (0.45)	34.41 (4.14)	65.59 (4.14)	-6.98 (1.26)	10.87 (0.63)	22.84	2.37
4-Factor	2.17 (0.71)	9.00 (0.43)	34.08 (3.74)	65.92 (3.74)	-6.75 (1.02)	10.46 (1.02)	23.43	2.49
5-Factor	2.47 (0.76)	9.40 (0.46)	33.21 (3.90)	66.79 (3.90)	-6.90 (1.19)	11.16 (1.19)	22.70	2.55
Hasan-Lo	2.87 (0.57)	9.91 (0.44)	31.16 (2.85)	68.84 (2.85)	-5.88 (0.78)	11.44 (0.78)	29.96	1.00
Fung-Hsieh	2.79 (0.68)	9.42 (0.44)	31.00 (3.37)	69.00 (3.37)	-6.65 (1.33)	11.34 (0.67)	26.31	2.59

TABLE V. Hedge Fund Performance Comparison under the Standard Models

Panel A: Average							
	CAPM	3-F	AMP	4-F	5-F	H-L	F-H
CAPM		0.38	0.37	0.46	0.16	-0.25	-0.16
3-Factor	-0.38		-0.01	0.08	-0.22	-0.62	-0.54
AMP	-0.37	0.01		0.09	-0.21	-0.62	-0.54
4-Factor	-0.46	-0.08	-0.09		-0.30	-0.70	-0.62*
5-Factor F5	-0.16	0.22	0.21	0.30		-0.40	-0.32
Hasan-LoL	0.25	0.62	0.62	0.70	0.40		0.08
Fung-Hsieh	0.16	0.54	0.54	0.62*	0.32	-0.08	

Panel B: Standard Deviation							
	CAPM	3-F	AMP	4-F	5-F	H-L	F-H
CAPM		0.05	-0.11	0.19	-0.21	-0.72*	-0.24
3-Factor	-0.05		-0.16	0.14	-0.27	-0.77*	-0.29
AMP	0.11	0.16		0.30	-0.10	-0.61	-0.13
4-Factor	-0.19	-0.14	-0.30		-0.40*	-0.91**	-0.43
5-Factor	0.21	0.27	0.10	0.40*		-0.51	-0.02
Hasan-Lo	0.72*	0.77*	0.61	0.91**	0.51		0.48
Fung-Hsieh	0.24	0.29	0.13	0.43	0.02	-0.48	

Panel C: Proportion of Positive Alphas							
	CAPM	3-F	AMP	4-F	5-F	H-L	F-H
CAPM		1.97	2.76*	2.42*	1.56	-0.50	-0.66
3-Factor	-1.97		0.78	0.45	-0.42	-2.47	-2.63
AMP	-2.76*	-0.78		-0.33	-1.20	-3.25	-3.42
4-Factor	-2.42*	-0.45	0.33		-0.87	-2.92	-3.08
5-Factor 5	-1.56	0.42	1.20	0.87		-2.05	-2.22
Hasan-Lo	0.50	2.47	3.25	2.92	2.05		-0.16
Fung-Hsieh	0.66	2.63	3.42	3.08	2.22	0.16	

Panel D: 10th Percentile							
	CAPM	3-F	AMP	4-F	5-F	H-L	F-H
CAPM		0.59***	0.53***	0.31	0.45*	-0.56	0.20
3-Factor	-0.59***		-0.06	-0.28**	-0.13	-1.15	-0.38*
AMP	-0.53***	0.06		-0.22	-0.08	-1.09	-0.33
4-FactorA	-0.31	0.28**	0.22		0.14	-0.87	-0.11
5-Factor	-0.45*	0.13	0.08	-0.14		-1.01	-0.25
Hasan-Lo	0.56	1.15	1.09	0.87	1.01		0.76
Fung-Hsieh	-0.20	0.38*	0.33	0.11	0.25	-0.76	

Panel E: 90th Percentile							
	CAPM	3-F	AMP	4-F	5-F	H-L	F-H
CAPM		0.36*	0.22	0.62**	-0.08	-0.36	-0.26
3-Factor	-0.36*		-0.15	0.26***	-0.44**	-0.72	-0.62***
AMP	-0.22	0.15		0.41	-0.29	-0.57	-0.47*
4-FactorA	-0.62**	-0.26***	-0.41		-0.70***	-0.98	-0.88***
5-Factor 5	0.08	0.44**	0.29	0.70***		-0.28	-0.18
Hasan-Lo	0.36	0.72	0.57	0.98	0.28		0.10
Fung-Hsieh	0.26	0.62***	0.47*	0.88***	0.18	-0.10	

TABLE VI. Alternative Factors for Equity Funds

	Moments		Proportions		Quantiles		Specif. Stats	
Panel A: Impact of the Factors on Performance								
	Mean(Ann.)	Std(Ann.)	Negative	Positive	10%(Ann.)	90%(Ann.)	Av.R^2	GOS
CAPM	2.06 (0.94)	8.19 (0.51)	33.45 (5.07)	66.55 (5.07)	-6.47 (1.36)	10.29 (1.36)	26.31	3.74
CAPM + Factors	0.36 (0.92)	10.09 (0.52)	47.14 (4.65)	52.86 (4.65)	-9.13 (1.63)	9.60 (1.22)	33.53	3.12
Difference	1.70*** (0.61)	-1.90*** (0.55)	-13.70*** (3.11)	13.70*** (3.11)	2.66*** (0.73)	0.69 (0.73)		
Panel B: Return Premium for Each Factor								
	Moments		Proportions		Quantiles		Correlation	
	Mean(Ann.)	Std(Ann.)	Negative	Positive	10%(Ann.)	90%(Ann.)	Factors	Alpha
Correlation	0.18	6.11	42.59	57.41	-2.75	3.18	-0.11	-0.23
Variance	0.43	5.21	45.40	54.60	-2.55	3.96	-0.10	-0.21
Liquidity	0.23	1.62	40.48	59.52	-0.88	1.55	0.02	-0.13
Betting Against Beta	0.04	4.16	44.88	55.12	-3.20	3.17	-0.07	-0.28
Equity Carry	0.27	1.92	44.40	55.60	-1.40	2.13	0.01	-0.16
Equity TS Momentum	0.56	2.38	39.72	60.28	-1.09	2.82	0.01	-0.12
Average	0.28	3.57	42.91	57.09	-1.98	2.80	-0.04	-0.19

TABLE VII. Alternative Factors for Macro Funds

	Panel A: Impact of the Factors on Performance							
	Moments		Proportions		Quantiles		Specif. Stats	
	Mean(Ann.)	Std(Ann.)	Negative	Positive	10%(Ann.)	90%(Ann.)	Av.R^2	GOS
CAPM	3.32 (1.19)	11.59 (1.05)	32.16 (4.32)	67.84 (4.32)	-7.44 (1.37)	13.75 (2.06)	8.45	4.23
CAPM + Factors	-0.56 (1.06)	13.44 (1.09)	54.67 (4.59)	45.33 (4.59)	-12.42 (1.47)	10.62 (1.47)	20.36	2.66
Difference	3.88^{***} (0.93)	-1.85^{*} (0.95)	-22.50^{***} (3.89)	22.50^{***} (3.89)	4.99^{***} (0.71)	3.13 (2.12)		

	Panel B: Return Premium for Each Factor							
	Moments		Proportions		Quantiles		Correlation	
	Mean(Ann.)	Std(Ann.)	Negative	Positive	10%(Ann.)	90%(Ann.)	Factors	Alpha
Equity Carry	0.17	2.11	44.68	55.32	-1.60	2.05	-0.03	-0.09
Bond Carry (level)	0.50	2.79	40.20	59.80	-1.77	3.02	-0.01	-0.17
Bond Carry (slope)	0.28	2.88	44.31	55.69	-2.09	2.80	-0.01	-0.20
Commodity Carry	0.10	2.14	42.76	57.24	-1.18	1.52	0.01	-0.34
Currency Carry	-0.10	2.17	53.08	46.92	-1.95	1.47	-0.03	-0.09
Equity TS Mom.	0.46	2.32	43.05	56.95	-1.16	2.73	0.03	-0.24
Bond TS Mom.	1.15	4.04	37.51	62.49	-2.32	5.36	0.04	-0.30
Commodity TS Mom.	0.59	3.29	38.36	61.64	-1.47	3.41	-0.03	-0.06
Currency TS Mom.	0.73	2.73	33.06	66.94	-1.04	3.05	0.02	-0.16
Average	0.43	2.72	41.89	58.11	-1.62	2.82	0.00	-0.18

TABLE VIII. Alternative Factors for Arbitrage Funds

Panel A: Impact of the Factors on Performance

	Moments		Proportions		Quantiles		Specif. Stats	
	Mean(Ann.)	Std(Ann.)	Negative	Positive	10%(Ann.)	90%(Ann.)	Av.R^2	GOS
CAPM	2.80 (0.76)	7.75 (0.46)	28.32 (4.29)	71.68 (4.29)	-5.63 (1.44)	10.13 (0.72)	17.68	4.78
CAPM + Factors	1.39 (0.67)	9.05 (0.58)	37.72 (3.42)	62.28 (3.42)	-8.32 (1.43)	9.59 (0.57)	24.47	3.48
Difference	1.41^{**} (0.57)	-1.30^{***} (0.38)	-9.40^{***} (3.14)	9.40^{***} (3.14)	2.69^{***} (0.31)	0.54^{*} (0.31)		

Panel B: Return Premium for Each Factor

	Moments		Proportions		Quantiles		Correlation	
	Mean(Ann.)	Std(Ann.)	Negative	Positive	10%(Ann.)	90%(Ann.)	Factors	Alpha
Correlation	-0.10	3.47	48.65	51.35	-2.08	2.18	-0.13	-0.26
Variance	0.69	3.43	33.17	66.83	-1.33	3.34	-0.07	-0.07
Liquidity	0.12	1.18	43.27	56.73	-0.64	0.94	-0.05	-0.19
Bond Carry (level)	0.42	1.63	36.94	63.06	-0.96	2.26	0.01	-0.24
Bond Carry (slope)	0.28	1.79	41.74	58.26	-1.22	1.96	0.01	-0.27
Average	0.28	2.30	40.75	59.25	-1.25	2.14	-0.05	-0.21

TABLE IX. Performance Comparison under the New Model

Panel A: All Funds

	Moments		Proportions		Quantiles		Spec. Stats	
	Mean(Ann.)	Std(Ann.)	Negative	Positive	10%(Ann.)	90%(Ann.)	Av.R^2	GOS
New Model	-0.07 (0.75)	11.54 (0.50)	48.15 (3.37)	51.85 (3.37)	-11.23 (1.71)	9.84 (0.57)	27.91	2.18
Difference								
vs CAPM	-2.70*** (0.59)	2.35*** (0.62)	16.49*** (2.93)	-16.49*** (2.93)	-4.79*** (0.91)	-1.24*** (0.45)		
vs 4-Factor	-2.24*** (0.59)	2.54*** (0.50)	14.07*** (2.86)	-14.07*** (2.86)	-4.48*** (1.13)	-0.62 (0.75)		
vs 5-Factor	-2.54*** (0.64)	2.14*** (0.53)	14.93*** (3.07)	-14.93*** (3.07)	-4.33*** (0.70)	-1.32* (0.70)		
vs Fung-Hsieh	-2.86*** (0.62)	2.11*** (0.53)	17.15*** (2.96)	-17.15*** (2.96)	-4.58*** (1.10)	-1.50*** (0.37)		

Panel B: Equity Funds

	Moments		Proportions		Quantiles		Spec. Stats	
	Mean(Ann.)	Std(Ann.)	Negative	Positive	10%(Ann.)	90%(Ann.)	Av.R^2	GOS
New Model	-0.18 (0.92)	10.47 (0.53)	50.04 (4.33)	49.96 (4.33)	-10.28 (1.37)	9.69 (0.92)	33.81	2.59
Difference								
vs CAPM	-2.24*** (0.68)	2.28*** (0.60)	16.59*** (3.53)	-16.59*** (3.53)	-3.81*** (0.75)	-0.60 (1.13)		
vs 4-Factor	-1.79*** (0.67)	2.59*** (0.50)	13.62*** (3.29)	-13.62*** (3.29)	-3.62*** (0.75)	0.41 (0.75)		
vs 5-Factor	-2.36*** (0.75)	2.13*** (0.58)	15.49*** (3.70)	-15.49*** (3.70)	-3.94*** (1.04)	-0.90 (0.69)		
vs Fung-Hsieh	-2.55*** (0.71)	2.24*** (0.54)	17.67*** (3.51)	-17.67*** (3.51)	-3.77*** (1.06)	-0.91 (1.06)		

Panel C: Macro Funds

	Moments		Proportions		Quantiles		Spec. Stats	
	Mean(Ann.)	Std(Ann.)	Negative	Positive	10%(Ann.)	90%(Ann.)	Av.R^2	GOS
New Model	-1.49 (1.12)	14.73 (1.01)	56.26 (3.82)	43.74 (3.82)	-15.52 (2.29)	10.74 (1.14)	19.47	2.69
Difference								
vs CAPM	-4.81*** (1.01)	3.14*** (1.22)	24.09*** (3.78)	-24.09*** (3.78)	-8.08*** (2.20)	-3.02* (1.76)		
vs 4-Factor	-4.05*** (1.03)	3.35*** (1.01)	20.14*** (3.99)	-20.14*** (3.99)	-7.36*** (1.68)	-2.33** (1.01)		
vs 5-Factor	-4.03*** (1.08)	2.85*** (1.03)	19.77*** (4.38)	-19.77*** (4.38)	-6.66*** (1.98)	-2.51** (0.99)		
vs Fung-Hsieh	-4.77*** (1.04)	2.52** (1.10)	24.01*** (3.94)	-24.01*** (3.94)	-7.54*** (2.11)	-2.97*** (1.06)		

Panel D: Arbitrage Funds

	Moments		Proportions		Quantiles		Spec. Stats	
	Mean(Ann.)	Std(Ann.)	Negative	Positive	10%(Ann.)	90%(Ann.)	Av.R^2	GOS
New Model	1.53 (0.68)	8.95 (0.67)	36.94 (3.78)	63.06 (3.78)	-6.89 (1.37)	9.44 (0.69)	27.19	3.20
Difference								
vs CAPM	-1.27** (0.61)	1.20** (0.53)	8.61** (3.44)	-8.61** (3.44)	-1.26* (0.67)	-0.69 (0.45)		
vs 4-Factor	-1.11* (0.60)	1.19** (0.50)	8.61** (3.52)	-8.61** (3.52)	-1.39** (0.68)	-0.40* (0.23)		
vs 5-Factor	-1.30** (0.62)	0.94* (0.50)	9.15*** (3.45)	-9.15*** (3.45)	-1.45 (0.94)	-0.86 (0.70)		
vs Fung-Hsieh	-1.41** (0.57)	1.19** (0.58)	9.36*** (3.36)	-9.36*** (3.36)	-1.43 (0.88)	-0.64 (0.66)		

TABLE X. Performance Comparison under the New Model – Robustness Analysis

Panel A: Multi-Strategy

	Moments		Proportions		Quantiles		Spec. Stats	
	Mean(Ann.)	Std(Ann.)	Negative	Positive	10%(Ann.)	90%(Ann.)	Av.R^2	GOS
New Model	-0.79 (0.90)	10.25 (0.72)	49.78 (3.84)	50.22 (3.84)	-11.49 (1.93)	9.25 (0.77)	28.54	0.80
Difference								
vs CAPM	-2.92*** (0.73)	1.20 (0.82)	20.04*** (3.98)	-20.04*** (3.98)	-4.47*** (0.80)	-1.19** (0.53)		
vs 4-Factor	-2.63*** (0.68)	1.30* (0.70)	16.08*** (3.88)	-16.08*** (3.88)	-3.80*** (0.88)	-1.36*** (0.39)		
vs 5-Factor	-3.21*** (0.78)	0.50 (1.21)	18.94*** (4.27)	-18.94*** (4.27)	-3.76*** (0.82)	-1.96*** (0.61)		
vs Fung-Hsieh	-3.22*** (0.72)	0.67 (0.93)	20.26*** (3.45)	-20.26*** (3.45)	-4.74*** (0.90)	-1.39* (0.72)		

Panel B: Funds of Funds

	Moments		Proportions		Quantiles		Spec. Stats	
	Mean(Ann.)	Std(Ann.)	Negative	Positive	10%(Ann.)	90%(Ann.)	Av.R^2	GOS
New Model	-3.48 (1.03)	6.99 (0.50)	75.25 (6.41)	24.75 (6.41)	-10.72 (2.02)	2.53 (0.90)	44.13	11.77
Difference								
vs CAPM	-3.74*** (0.95)	1.22** (0.52)	34.99*** (8.83)	-34.99*** (8.83)	-5.20*** (1.61)	-2.74*** (0.54)		
vs 4-Factor	-3.11*** (0.79)	1.29*** (0.47)	28.60*** (7.66)	-28.60*** (7.66)	-4.71*** (1.09)	-2.01*** (0.65)		
vs 5-Factor	-3.71*** (0.92)	1.23*** (0.47)	34.34*** (8.89)	-34.34*** (8.89)	-5.48*** (1.16)	-2.64*** (0.92)		
vs Fung-Hsieh	-4.11*** (0.89)	1.12** (0.52)	38.39*** (7.59)	-38.39*** (7.59)	-5.48*** (1.28)	-3.60*** (0.77)		

Panel C: Sub Period January 1994 to June 2005 (first 138 observations)

	Moments		Proportions		Quantiles		Spec. Stats	
	Mean(Ann.)	Std(Ann.)	Negative	Positive	10%(Ann.)	90%(Ann.)	Av.R^2	GOS
New Model	1.66 (1.49)	14.83 (1.01)	39.90 (5.05)	60.10 (5.05)	-12.58 (2.98)	14.77 (1.79)	22.89	1.16
Difference								
vs CAPM	-4.87*** (1.26)	4.51*** (1.14)	22.95*** (4.18)	-22.95*** (4.18)	-9.80*** (2.32)	-2.28 (1.93)		
vs 4-Factor	-3.16** (1.49)	4.49*** (1.01)	16.57*** (5.12)	-16.57*** (5.12)	-8.35*** (1.91)	-0.11 (1.91)		
vs 5-Factor	-3.57** (1.51)	3.89*** (1.06)	17.66*** (5.19)	-17.66*** (5.19)	-7.99*** (2.23)	-1.08 (1.86)		
vs Fung-Hsieh	-4.06*** (1.43)	5.07*** (0.97)	21.06*** (4.86)	-21.06*** (4.86)	-9.26*** (2.48)	-0.72 (1.42)		

Panel D: Sub Period July 2005 to December 2016 (last 138 observations)

	Moments		Proportions		Quantiles		Spec. Stats	
	Mean(Ann.)	Std(Ann.)	Negative	Positive	10%(Ann.)	90%(Ann.)	Av.R^2	GOS
New Model	-0.20 (0.90)	9.95 (0.52)	50.03 (4.41)	49.97 (4.41)	-10.18 (1.37)	9.04 (0.91)	32.28	2.61
Difference								
vs CAPM	-1.71** (0.74)	1.11* (0.65)	10.97** (4.34)	-10.97** (4.34)	-2.73*** (0.88)	-0.48 (0.44)		
vs 4-Factor	-1.56** (0.65)	1.43*** (0.55)	10.41*** (3.78)	-10.41*** (3.78)	-2.84*** (1.00)	-0.21 (0.67)		
vs 5-Factor	-2.04*** (0.74)	1.16** (0.54)	13.10*** (3.99)	-13.10*** (3.99)	-2.96*** (0.99)	-1.01 (0.66)		
vs Fung-Hsieh	-2.10*** (0.69)	0.66 (0.58)	13.07*** (3.86)	-13.07*** (3.86)	-2.66** (1.06)	-1.21* (0.70)		

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