The Economic Value and Statistical Properties of Manipulation-proof Performance Measures*

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Abstract

In this paper, we analyze the economic and the statistical properties of manipulation-proof performance measure (MPPM) proposed by Goeztmann, Ingersoll, Spiegel, and Welch (2007). Specifically, we propose a novel way to incorporate macroeconomic information into the accurate estimation of conditional MPPMs. Our approach extends and exploits the recent developments in nonparametric estimation methods that are used in portfolio choice literature. Using a large consolidated hedge fund database, we demonstrate that a strategy based on the standard MPPM delivers poor out-of-the sample performance with a significant downside risk. After allowing hedge fund MPPMs vary nonparametrically based on existing macroeconomic environment, we show that the conditional strategy delivers superior out-of-the-sample performance with a negligible tail risk. The performance of the conditional MPPM strategy is impressive relative to other strategies. It outperforms significantly strategies based on the traditional measures (e.g., the t-statistic of Fung and Hsieh (2004) alpha and Sharpe ratio) or recently proposed new measures (e.g., R^2 and Strategy Distinctness Index). Our results are robust across hedge fund size groups, even after taking into account typical hedge fund data biases and redemption restrictions associated with portfolio rebalancing.

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1 Introduction

The aim of this paper is to extend recent unconditional manipulation proof performance measures (MPPM) to incorporate predictive variables and to study the empirical performance of unconditional and conditional MPPMs. In their seminal study, Goetzmann, Ingersoll, Spiegel, and Welch (2007) (henceforth, GISW) propose a measure (MPPM) that is carefully theoretically motivated and less vulnerable than other measures to simple dynamic manipulation strategies. Can investors use such a measure ex ante to create portfolios of hedge funds that generate superior performance ex post? Given recent evidence[1] that predictive variables can be used to improve hedge fund selection, would a conditional version of the MPPM perform even better out-of-sample? As the study by GISW (2007) does not address these important questions, we fill this important research gap. Despite its theoretical appeal, we show that the standard MPPM fails to predict hedge funds' future performance. In contrast, our novel nonparametric approach to incorporate macroeconomic information into the estimation of MPPM is associated with superior hedge fund performance predictability.

Standard financial economics text books propose that the investment manager's performance should be measured using Sharpe ratio or alpha. To evaluate the performance of traditional mutual funds is relatively straightforward compared to measuring the performance of complex investment strategies employed by hedge funds (Kosowski, Naik, and Teo (2007), Bollen and Pool (2008), (2009), Patton, Ramadorai and Streatfield, 2011). The complexity of hedge fund strategies makes benchmarking their returns particularly challenging and raises the possibility of model misspecification. Investment managers have an obvious incentive to take actions that enhance performance measures. In doing so investment managers can increase a fund's performance measure, either through effort and application of skill, or through "information-free" activities that do not actually add value for the fund's investor. In particular, "information-free" investing can be seen as a way to emphasize that it is not based upon the production and deployment of value-relevant information about the underlying assets in the portfolio. Due to the flexible investment mandate of hedge funds,

[1] See, for example, Avramov, Kosowski, Naik, and Teo (2010), Avramov, Barras, and Kosowski (2012).

it is well-known (e.g., Weisman (2002)) that some hedge funds engage in information-free investing.

To avoid the manipulation of standard performance measures, GISW (2007) propose a measure that cannot be enhanced using "information-free" investing. Several recent studies (e.g., Bali, Brown, and Caglayan (2011), Titman and Tiu (2011), and Sun, Wang, and Zheng (2011) evaluate hedge fund ex-post performance using the MPPM since hedge funds are relatively unconstrained in their derivatives use and have option-like incentive structures (Almazan, Brown, Carlson, and Chapman (2004), Brunnermeier and Pedersen (2009)). However, to the best of our knowledge, there is no study that employs the MPPM measure to predict hedge fund performance. Such an exercise would shed further light how hedge funds engage "information-free" investing to increase their performance measures. While the MPPM has been shown to be a theoretically superior ex-post performance measure, there is so far no evidence on whether the use of the MPPM leads to performance persistence ex post when the MPPM is used to sort funds ex ante.

We make several contributions in this paper. It is well-known that the MPPM is theoretically superior compared to standard measures such as Sharpe ratio and alpha, but little is known about the econometric properties of the MPPM. Our first contribution is therefore to analyze the economic and statistical properties of the MPPM using a large consolidated hedge fund database. Specifically we develop statistical significance tests for the unconditional and conditional MPPM, which we label *standardized* (conditional and unconditional) MPPM.

Second, we propose a new way to estimate a conditional MPPM using a nonparametric approach. Specifically, to estimate the MPPM precisely, we apply kernel regression techniques. To demonstrate the superiority of a new conditional MPPM estimator, we predict hedge fund performance by incorporating predictability based on a set of macroeconomic variables. One novel aspect of our approach is the use of a copula transform that allows us to exploit dependencies between macroeconomic variables and removes the noise in the marginal distributions of the macroeconomic variables. We can exploit a large set of macroeco-

nomic variables, which are documented, to predict hedge fund performance (e.g., Avramov, Kosowski, Naik, and Teo (2010)) or shifts in hedge fund systemic risk loadings (e.g., Patton and Ramadorai (2010)). In particular, our set of predictors contains the default spread, the term and TED spreads, the change in 3-month T-bill rate, aggregate hedge-fund industry flows, volatility measures (both VIX and variance risk premium), and lagged return on S&P500 index and its dividend yield. We apply a nonparametric regression framework so that conditional MPPMs involve locally weighted averages, where localization is done in the state space of historical macroeconomic information. The state space localization is analogous to the time space localization which is used in moving averages. Moving averages are often ad-hoc, but our novel MPPM estimators are based on statistical techniques that can be motivated by economic theory.

Third, we study the economic value of the unconditional and conditional MPPM strategies. Our results suggest that standard MPPM fails to predict consistently hedge fund future performance. Indeed, a strategy based on the unconditional MPPMs delivers poor out-of-the-sample performance with a significant tail risk. In contrast, a strategy based on our novel conditional MPPMs, which vary nonparametrically based on the macroeconomic state, delivers superior out-of-the-sample performance. In particular, the basic and standardized conditional MPPM strategies provide statistically and economically significant performance predictability. The basic conditional MPPM strategy earns superior returns, alphas and MPPMs, while its standardized version delivers extremely high Sharpe and information ratios. Importantly, the outstanding performance is not associated with performance manipulation and significant downside risk, since the MPPMs are extremely high and expected shortfalls relatively low in respect to hypothetically earned profits.

Importantly, from the perspective of economic value, a conditional strategy based on the nonparametric MPPM delivers superior predictability among large funds and even at annual horizons. The magnitude of predictability is superior to standard measures based on the t-statistic of Fung and Hsieh (2004) alpha or other new methods including the Titman and Tiu (2011)'s R^2 and Sun, Wang and Zheng (2010)'s *SDI*.

Our paper is related to three streams of literature. First, we add to literature on hedge fund performance and its persistence. Using sophisticated econometric methods, recent literature (e.g., Kosowski, Naik, and Teo (2007) and Jagannathan, Malakhov, and Nokikov (2010)) has shown that hedge fund performance persists at annual horizons. Titman and Tiu (2011) show that skilled managers choose to hedge away systemic risks and therefore, have a lower R^2 with respect to systematic risk factors. Based on Strategy Distinctness Index (SDI), Sun, Wang, and Zheng (2011) show that skilled managers are more likely to pursue unique investment strategies delivering superior risk-adjusted performance. We contribute to this literature by showing that hedge fund performance persistence can be significantly improved by relying on conditional MPPM that turns out to be superior over the other performance measures in predicting hedge fund performance.

Second, nonparametric methods are used successfully in choosing optimal portfolio and asset pricing, while not in predicting investment fund performance. Specifically, Aït-Sahalia and Brandt (2001), Brandt (1999) and Györfi, Lugosi, and Udina (2006) choose directly optimal portfolio weights without modelling conditional return distribution using nonparametric methods. Wang (2003) propose a new conditional asset pricing test based on non-parametric methods. We contribute to these nonparametric methods by using a copula transformation that allows us to better exploit dependencies between macroeconomic variables in predicting hedge fund performance.

Finally, this paper relates to literature examining hedge fund manipulation, misreporting, and strategic reporting behavior. The recent studies (e.g., Bollen and Pool (2009), Patton, Ramadorai, and Streatfield (2011), and Aragon and Nanda (2011)) show that hedge funds misreport, revisit, and strategically delay their returns when reporting in commercial databases. In the next version, we aiming at adding to this literature by explicitly linking performance manipulation on hedge funds' options usage and risk-taking.

The paper is structured as follows. Section 2 focuses on the statistical properties of MPPM. Section 3 provides the empirical results. In Section 4, we give a conclusion.

2 Measuring hedge fund performance using MPPM

This section presents performance measures used in the study. We propose a new way to measure investment manager performance under manipulation-proof conditions. In particular, we build on the GISW (2007) manipulation-proof performance measures. We extend it by proposing two new statistical estimators based on the economic theory. First, we take the estimation error into account in the estimation of the MPPM. Second, we incorporate nonparametrically macroeconomic information into the estimation of the MPPM in order to obtain accurate predictions about future MPPM realizations.

2.1 Basic unconditional MPPM

Our first performance measure is the basic MPPM based on GISW (2007). Let $r_1, \ldots, r_T$ be the observed net returns of a hedge fund. Denote

$$Y_t = \left(\frac{1 + r_t}{1 + r_{ft}} \right)^{1-\rho}, \tag{1}$$

where $\rho > 1$ and $r_{f1}, \ldots, r_{fT}$ are the net returns of a risk free investment. Parameter ρ is a risk aversion parameter and larger values of ρ are used in the performance measure when the investor is more risk averse. Following the practise in the literature, we set risk aversion equal to three.[2] The basic MPPM based on DISW (2007) is defined as

$$\text{MPPM} = \frac{1}{(1-\rho)\Delta t} \log \left(\frac{1}{T} \sum_{t=1}^{T} Y_t \right),$$

where $\Delta t = 1/12$ for the monthly hedge fund data

Next, we propose the *Standardized MPPM* that takes estimation error into account. Let

$$\hat{\mu} = \frac{1}{T} \sum_{t=1}^{T} Y_t,$$

[2] Unreported robustness checks show that the results are not sensitive to the choice of risk aversion coefficient.

$$\hat{\sigma}^2 = \frac{1}{T}\sum_{t=1}^{T} Y_t^2 - \hat{\mu}^2,$$

and[3]

$$\sigma(\text{MPPM}) = \frac{1}{(1-\rho)\Delta t}\,\frac{\hat{\sigma}/\sqrt{T}}{\hat{\mu}}\,.$$

Define *Standardized MPPM* such as

$$\text{Stand-MPPM} = \frac{\text{MPPM}}{\sigma(\text{MPPM})}\,.$$

Intuitively, the estimation error is taken into account by dividing the point estimate of the MPPM by its estimation uncertainty.

2.2 Nonparametric conditional MPPM

Next, We apply a nonparametric regression framework so that conditional MPPMs involve locally weighted averages, where localization is done in the state space of historical macroeconomic information. The state space localization is analogous to the time space localization which is used in moving averages. Moving averages are often ad-hoc, but our novel MPPM estimators are based on statistical techniques that can be motivated by economic theory.

Formally, to estimate the *Conditional MPPM* , let $Z_1, \ldots, Z_T \in \mathbf{R}^d$ be the observed relevant macroeconomic information set. Define *Conditional MPPM* in the following way

$$\text{C-MPPM} = \frac{1}{(1-\rho)\Delta t}\,\log\left(\sum_{t=2}^{T} p_t(Z_T)\,Y_t\right),$$

where

$$p_t(Z_T) = \frac{K_h(Z_{t-1} - Z_T)}{\sum_{i=2}^{T} K_h(Z_{i-1} - Z_T)}\,,$$

$K_h(x) = K(x/h)/h^d$ is the scaled kernel function, $K : \mathbf{R}^d \to \mathbf{R}$ is the kernel function, and $h > 0$ is the smoothing parameter.

[3] We can approximate $\text{Var}(g(X)) \approx [g'(\mu)]^2\sigma^2$, where $\mu = EX$ and $\sigma^2 = \text{Var}(X)$. Thus $\text{Var}(g(\bar{X})) \approx [g'(\mu)]^2\sigma^2/T$, where $\bar{X} = \sum_{t=1}^{T} X_t/T$. When $g(x) = \log(x)$, then $g'(x) = 1/x$ and $\text{Var}(\log(\bar{X})) \approx \sigma^2/(T\mu^2)$.

We also estimate the *Conditional standardized MPPM.* Let

$$\hat{\mu}_c = \sum_{t=2}^{T} p_t(Z_t)\, Y_t,$$

$$\hat{\sigma}_c^2 = \sum_{t=2}^{T} p_t(Z_t)\, Y_t^2 - \hat{\mu}_c^2,$$

and

$$\sigma(\text{c.MPPM}) = \frac{1}{|1-\rho|\,\Delta t}\,\frac{\hat{\sigma}_c\sqrt{\sum_{t=2}^{T} p_t(Z_t)^2}}{\hat{\mu}_c}\,.$$

Then, define the *Conditional standardized MPPM* as

$$\text{C-Stand-MPPM} = \frac{\text{c.MPPM}}{\sigma(\text{c.MPPM})}\,.$$

The conditional MPPM is a normalized logarithm of a weighted average of the past values of Y_t and the weight $p_t(Z_T)$ is large at those points in time t when the relevant information Z_t available at that time is close to the current relevant information Z_T, that is, the weight $p_t(Z_T)$ is large at those points in time t when economic conditions as described by the macro variables are similar to the current situation. Smoothing parameter h controls the degree of similarity so that for a small h only very similar situations are taken into account whereas for a large h also less similar situations are taken into account when calculating the weighted average. We set h in our baseline application equal to one.[4]

When we use kernel weights with a single smoothing parameter h for each component of Z_t, it is important that the components of Z_t are standardized so that their scales are roughly the same. For example, a simple standardization would be to make the sample standard deviations of the components of Z_t equal to one: let $Z_t^0 = (Z_{t,1}^0, \ldots, Z_{t,d}^0)$ be the original measurements and define

$$Z_t = \left(Z_{t,1}^0/s_{t,1}, \ldots, Z_{t,d}^0/s_{t,d}\right),$$

[4] Unreported robustness tests show that the results are not sensitive to the choice of bandwidth.

where $s_{t,l}^2 = t^{-1}\sum_{u=1}^{t}(Z_{u,l}^0 - \bar{Z}_{t,l}^0)^2$, $\bar{Z}_{t,l}^0 = t^{-1}\sum_{u=1}^{t} Z_{u,l}^0$, for $l = 1, \ldots, d$. We have used the standardization

$$Z_t = \left(\Phi^{-1}(Z_{t,1}^1), \ldots, \Phi^{-1}(Z_{t,d}^1)\right), \tag{2}$$

where $\Phi : \mathbf{R} \to [0,1]$ is the distribution function of the standard normal distribution,

$$Z_{t,l}^1 = \frac{\text{rank}(Z_{t,l}^0)}{t+1},$$

and

$$\text{rank}(Z_{t,l}^0) = \#\{Z_{u,l}^0 : Z_{u,l}^0 \leq Z_{t,l}^0, \;\; u = 1, \ldots, t\},$$

where notation $\#A$ denotes the number of elements of set A. This transformation makes the distribution of the components of Z_t approximately standard normal but it does not change the copula (joint distribution) of the components of Z_t^0.

The relevant information $Z_t \in \mathbf{R}^d$ is a vector that contains information about relevant macro variables and also about their immediate past. For example, we might have m relevant macro variables $W_{t,1}, \ldots, W_{t,m}$ and then we take into account $k \geq 1$ previous values of the macro variables and put

$$Z_t^0 = (W_{t,1}, \ldots, W_{t-k,1}, \ldots, W_{t,m}, \ldots, W_{t-k,m}) \in \mathbf{R}^d,$$

where $d = mk$, and then Z_t is obtained by (2).

Finally, it is important to note that we overcome the "curse of dimensionality" using completely nonparametric kernel regression. The curse of dimensionality refers in the context of kernel regression to the fact that the rate of convergence of the estimator to its asymptotic distribution deteriorates exponentially with the number of regressors. According to Aït-Sahalia and Brandt (2001), given the relatively short sample, one cannot reliably estimate the conditional expectation with a nonparametric estimator for more than two predictors. To overcome this econometric problem, they adopt a semiparametric approach. However, new evidence presented in Györfi, Lugosi and Udina (2006) and in our empirical section

shows that even completely nonparametric kernel regression can be used efficiently in time series prediction.

3 Empirical Results

3.1 Data description and performance measures

Using a large consolidated hedge fund database, we estimate hedge fund performance measures. The aggregate data set contains hedge funds from BarclayHedge, Hedge Fund Research (HFR) and Lipper TASS databases. We merge databases using the novel merging procedure proposed by Joenväärä, Kosowski, and Tolonen (2012). The raw data set contains 16,449 unique hedge funds having at least 12 monthly return observations.

For each individual hedge fund having at least 24 return observations, we estimate unconditional MPPMs (*MPPM*) and its standardized version (*Stand-MPPM*), which takes estimation error into account. Following the practise in the literature, we set the risk aversion coefficient equal to three. We then estimate the conditional MPPMs using the whole return history of each individual hedge fund. Both the conditional MPPM (*C-MPPM*) and its standardized version (*C-Stand-MPPM*) are estimated using a nonparametric kernel regression provided in the methodological part.

As macro economic variables, we use term spread, default spread, volatility, dividend yield, TED spread and aggregate flow as well as lagged S&P 500 and its dividend yield. Our choice of predictor variables is based on several studies that have used these variables to predict hedge fund performance (e.g., Avramov, Kosowski, Naik, and Teo (2011)) or shifts in hedge fund systemic risk loadings (e.g., Patton and Ramadorai (2011)). We also estimate standard performance measures such as alpha and Sharpe ratio. Hedge fund alphas are estimated using the Fung and Hsieh (2004) seven-factor model, which is common in many hedge fund performance studies. We focus on the t-statistics of the Fung and Hsieh alpha (*t-stat of alpha*), since it has superior statistical properties compared to alpha (Kosowski,

Naik and Teo , 2007). The Fung and Hsieh model consists of the S&P 500 excess return, the Wilshire small cap minus large cap return, the excess return on the 10-year Treasury, the return spread of Moody's Baa minus 10-year Treasury, the bond PTFS, the currency PTFS, and the commodities PTFS, where PTFS is a primitive trend following strategy.

Table 1 presents descriptive statistics for different performance measures and rank correlations between performance measures. Overall, according to Table 1, performance measures' rank correlations are quite low, suggesting that the measures contain quite different information. Hence, fund rankings based on one measure are likely to be quite different from those based on another measure. The rank correlations are highest between *MPPM (C-MPPM)* and *Stand-MPPM* (*C-Stand-MPPM*), being 0.66 (0.61). This a natural result since the standardized MPPM is defined as the MPPM divided by its standard error. In contrast, rank correlations between unconditional and conditional MPPMs are relatively low ranging from 0.21 to 0.44. To compare how the information content of MPPMs differs from standard performance measures, we calculate rank correlations between MPPMs and t-statistic of alpha. We find that the rank correlation between the *C-Stand MPPM* and the *t-stat of alpha* is 0.78. Hence, these two measures contain similar types of information. However, the rank correlations of the t-statistic of alpha are low for other MPPM specifications.

[Insert Table 1 here]

The cross-sectional average of the unconditional MPPM is 2.48 percent per annum, while it is only 0.85 for the standardized version of the MPPM. The cross-sectional averages of conditional MPPMs across funds are slightly higher (3.89 percent and 0.59). For comparison we report the cross-sectional average of the alpha t-statistic (0.80). Cross-sectional standard deviations show that both MPPMs have the highest variation, while the t-statistic of alpha has the lowest cross-sectional variation.

3.2 Unconditional MPPMs and performance persistence

While GISW (2007) show that the MPPM is a theoretically superior performance measure, there is no comprehensive study that investigates how the MPPM predicts investment managers' future performance. To address this issue, we examine the investment performance of a strategy that ranks hedge funds based on their MPPMs. We also propose a new way to estimate MPPMs by taking estimation error into account. Specifically, we sort hedge funds on January 1 each year from 1996 to 2010 into portfolios, based on the basic and standardized MPPMs. We use the most recent 24 months of return observations preceding the evaluation period for each individual hedge fund's MPPM estimation. We rebalance portfolios on a yearly basis in order to take into account share restrictions in the form of lock up, notice and redemption periods.

Table 2 presents the performance persistence results for two unconditional strategies based on the MPPM and its standardized version. Panel A in Table 2 shows that the unconditional MPPM strategy performs poorly despite the fact that it should be theoretically superior. Indeed, for the standard MPPM strategy, the spread portfolios between the top and the bottom deciles across the wide range of performance measures are indistinguishable from zero. In addition, there is no monotonic relationship between the hedge fund's MPPM and future performance. Hence, with annual rebalancing, investors are not better off relying on the standard MPPM. Indeed, the strategy based on top MPPM funds is associated with the highest downside risk among the decile portfolios. The expected shortfall at 95% level is 9.43 per month. The magnitude is remarkable, since it is over 30 percent higher than the second highest expected shortfall.

[Insert Table2 here]

Panel B in Table 2 presents the results for the standardized MPPM strategy. At best, the results show weak performance persistence. Indeed, at the 10 percent significance level, the top decile's Sharpe and information ratios are higher than the ones obtained from holding the bottom decile of funds. However, the spread between the top and bottom deciles' MPPMs

is not statistically significant. In addition, the respective spreads for the average alpha and excess returns are indistinguishable from zero. To sum up, the standardized version of the MPPM works better than the basic MPPM, but still there is little evidence of performance persistence. This raises the question of whether the conditional MPPMs can be used to predict hedge funds' future performance successfully.

3.3 Conditional MPPMs and performance predictability

Next, we examine whether conditional MPPMs predict hedge funds' future performance. We estimate conditional MPPMs using kernel regressions that allow us to exploit information about the current state of macroeconomic environment in order to obtain more accurate rankings between hedge funds. We follow similar performance evaluation methodology as for the unconditional case. The only difference is that we use all the available return history to estimate MPPMsmore accurately. It is very a natural choice, since the methodology is based on the idea that the performance of the fund depends heavily on the macroeconomic environment. Indeed, a specific hedge fund trading strategy should work during the certain type of state of economy.

Figure 1 shows the cumulative returns for the strategies based in both unconditional and conditional way to estimate MPPMs. The figure shows that the top decile portfolio based on the conditional MPPM has the highest cumulative returns. The unconditional MPPM strategy has the second highest cumulative returns. However, the performance of the unconditional strategy is significantly lower compared to its conditional counterpart. The conditional MPPMs strategy seems also to have a lower downside risk than the unconditional strategy. It is interesting to note that the standardized conditional MPPM strategy seems to deliver the steadiest returns suggesting that risk averse investors would be willing to invest in it. Hence, it is interesting to examine more formally whether the conditional MPPM strategy is able to outperform.

[Insert Figure 1 here]

Table 3 presents the persistence tests for conditional MPPMs. The overall results show that the conditional MPPM strategy delivers significant outperformance. Specifically, both versions of conditional MPPMs provide statistically and economically significant performance persistence across the wide range of performance measures. The conditional MPPM strategy earns superior returns, alphas and MPPMs, while its standardized version delivers extremely high Sharpe and information ratios. Importantly, the outstanding performance is not associated with performance manipulation and significant downside risk, since the MPPMs are extremely high and expected shortfalls relatively low in respect to hypothetically earned profits.

[Insert Table 3 here]

Panel A in Table 3 displays a wide range of performance measures for the conditional MPPM strategy. We find that the spread between the top and bottom portfolios for the MPPM and the alpha are economically and statistically significant. Indeed, the average spread between the top and bottom Fung and Hsieh (2004) alpha is 9.34 percent per year. The spread portfolios' MPPM is also extremely high being 8.65 percent on an annual basis. Together with reasonable low expected shortfall, it suggests that the conditional MPPM strategy is not associated downside risk and performance manipulation.

Panel B in Table 3 presents the performance measures for the standardized conditional strategy. The results in Panel B show that the standardized strategy delivers extremely high performance measured in terms of return taken by a risk unit. Specifically, the top decile portfolio for standardized strategy earns an annual information (Sharpe) ratio equaling to 1.91 (1.84). It is important to note that both of these ratios can be manipulated. However, this seems not to be the case, since the top decile's (standardized) MPPM is economically and statistically significant being annually 8.05 (5.69) percent. Finally, comparing the performance of basic conditional MPPM strategy and its standardized version, one can conclude that the standardized version delivers steadier performance that would be the interest of the risk averse investor.

3.4 Hedge fund size and performance predictability

Although the conditional MPPM strategy seems to outperform, it is important to examine the pervasiveness of performance predictability across size groups. From a practical perspective, if the extreme performance predictability is associated with only the small hedge funds, investors might not be able to exploit predictability. From a general economic perspective, it is important to know whether performance predictability is not only associated with smaller hedge funds that do not suffer from capacity constraints. To investigate the issue, we categorize hedge funds on the three groups based on fund size. Size groups are formed on a yearly basis in each December. Within size categories hedge funds are sorted on January 1 each year from 1996 to 2010 into portfolios, based on their conditional MPPM and standardized conditional MPPM.

[Insert Figure 2 here]

Table 4 presents the results of performance predictability tests across size categories. The findings suggest that predictability exists consistently across size categories. Even large hedge funds' performance can be predicted using both versions of conditional MPPMs. The only difference between the size categories is that we document the lower average performance measures for larger hedge funds compared to the small one. Figure 2 highlights the issue. It is interesting to note that Joenväärä, Kosowski, and Tolonen (2012) show that hedge fund performance persistence based on the t-statistic of Fung and Hsieh (2004) alpha is significantly lower for large funds compared to small ones. Hence, our sophisticated conditional strategy seems to be interesting from a practical point of view.

[Insert Table 4 here]

Panel A in Table 4 presents the performance measures for the conditional MPPM strategy across size categories. Although, on average, performance measures are lower for the large hedge funds, top decile portfolios' performance is still outstanding suggesting that large funds' performance can also be predicted. Specifically, we find that the top decile portfolio's

annual alpha is 6.46 percent with the t-statistic of 1.95. Importantly, the top decile portfolio's MPPM is 5.56 percent per year suggesting that superior performance is not associated with performance manipulation.

Panel B in Table shows the results for the standardized conditional MPPM strategy across size categories. The findings suggest that the strategy delivers steady returns also for large funds. The magnitude and statistical significance of MPPM, Share and information ratios is substantial. We find that the expected shortfall at 95 confidence interval is only 2.33 per month. To conclude, the risk averse investor would take advantage of hedge fund predictability given the low risk level of the standardized conditional MPPM strategy.

3.5 Share restrictions and performance predictability

To exploit performance predictability in hedge fund returns, real-time investors must consider the impact of share restrictions that limit portfolio rebalancing possibilities. It is a serious issue that has been often ignored in the prior literature. However, Joenväärä, Kosowski, and Tolonen (2012) show that annual performance persistence based on the t-statistic of Fung and Hsieh (2004) alpha vanishes to quarterly horizons when the role of the share restrictions is taken properly into account. To address the issue, we investigate performance predictability using (i) semi-annual and (ii) annual rebalancing horizons so that the impact of share restrictions is not ignored. In particular, within each rebalancing horizon, we form hedge fund decile portfolios based on conditional MPPMs using only the feasible information. For the feasible semi-annual (annual) rebalancing strategy, we exclude the funds that have redemption and lockup periods longer that 6 (12) months. In addition, we exclude funds having notice periods longer than 3 months. This implies that we use 3 month lagged information to estimate MPPMs to mitigate the look-ahead bias. We label this strategy as a feasible, and compare its performance to baseline conditional MPPM strategy's performance ignoring the share restrictions.

[Insert Figure 3 here]

Figure 3 highlights the impact of share restrictions on the rebalancing possibilities. It shows the cumulative returns are significantly higher for the strategies that ignores the share restrictions that hinder rebalancing in practise. More formally, Table 5 presents the results for the feasible conditional MPPM strategies. The results show that feasible conditional strategies deliver significant performance predictability at semi-annual horizons. However, when the portfolios are rebalanced at annual horizons, we then cannot document any evidence about the performance predictability.

[Insert Table 5 here]

Table 5 show economically and statistically significant performance for a feasible conditional MPPM strategy. Specifically, the top decile portfolio's performance is outstanding and only slightly lower compared to the baseline case ignoring the share restrictions. Also, the spreads between top and bottom deciles are statistically significant suggesting that performance can be predicted at the semi-annual horizons even though the impact of share restriction is taken into account. In contrast, Table 5 provides clear evidence that there is no performance predictability at annual horizons. The performance of decile portfolios seems to be random. Indeed, some of the top decile portfolios deliver lower performance than the bottom ones. However, none of the spread is statistically significant.

Taken together, we document that both conditional MPPM strategies provides superior at semi-annual horizons. The annual performance predictability vanishes when the realistic portfolio rebalancing are implemented.

3.6 MPPM vs. other measures

To compare performance persistence of the MPPM strategy to the other famous ways to rank investment managers, we conduct the persistence tests based on the Fung and Hsieh (2004) alpha, its t-statistic, and R^2 as well as the Sharpe ratio. We opt these performance measures, since it is standard practice in literature to use the t-statistic of alpha in persistence tests. In a recent study, Titman and Tiu (2010) show that a low R^2 respect to systematic risk

factors is associated with superior future performance.[5] The Sharpe ratio is the most used performance measure among practitioners, and therefore, investment managers would like to deliver a superior Sharpe ratio for their investors.

[Insert Table 6 here]

Table 6 presents the performance persistence tests based on these four measures. The findings in Table 6 suggest that none of the strategies are capable to deliver such an outstanding performance over the conditional MPPM strategy. The magnitude of performance based on there four measures is similar to the one obtained using the unconditional MPPM strategy. Somehow this is not surprising, since the strategies do not rely on macroeconomic information, which has been proven to be important in predicting hedge fund future performance. However, it is not straightforward to incorporate macroeconomic information in estimating performance measures accurately. As a future extension, we consider to compare the performance of the conditional MPPM strategy to the performance of other conditional strategies, for example, those proposed by Avramov, Kosowski, Naik and Teo (2010), and Avramov, Barras, and Kosowski (2012) as well as Kosowski, Naik and Teo (2007).

4 Conclusions

In this paper, we analyze the economic and the statistical properties of the MPPM proposed by Goeztmann, Ingersoll, Spiegel, and Welch (2007). In particular, we propose a novel nonparametric way to incorporate macroeconomic information into the accurate estimation of conditional MPPMs. Our approach extends as well as exploits the recent developments in nonparametric estimation methods that are used in portfolio choice literature. Using a large consolidated hedge fund database, we demonstrate that a strategy based on the standard MPPM delivers poor out-of-the sample performance with significant downside risk. However

[5] In unreported robustness tests we examine the performance persistence tests based on the Strategy Distinctness Index (SDI) proposed by Sun, Wang, and Zheng (2011). Given that the SDI is closely related to R^2 we opt to show only the results for R^2 in Table 6.

when we allow the hedge fund's MPPMs vary nonparametrically based on macroeconomic state, we find that our novel conditional strategy delivers outstanding performance with insignificant tail risk. Importantly, from a practical point of view, we demonstrate that our findings are robust across hedge fund size groups as well as redemption restrictions associated with portfolio rebalancing. We are currently working on an revision of this paper in which we aim at linking MPPM measures to option based risk taking. Using a unique data about hedge fund option holdings, we expect to find a link between "information less" performance manipulation and usage of certain types of options.

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Figure 1: Cumulative Returns to top decile MPPM portfolios

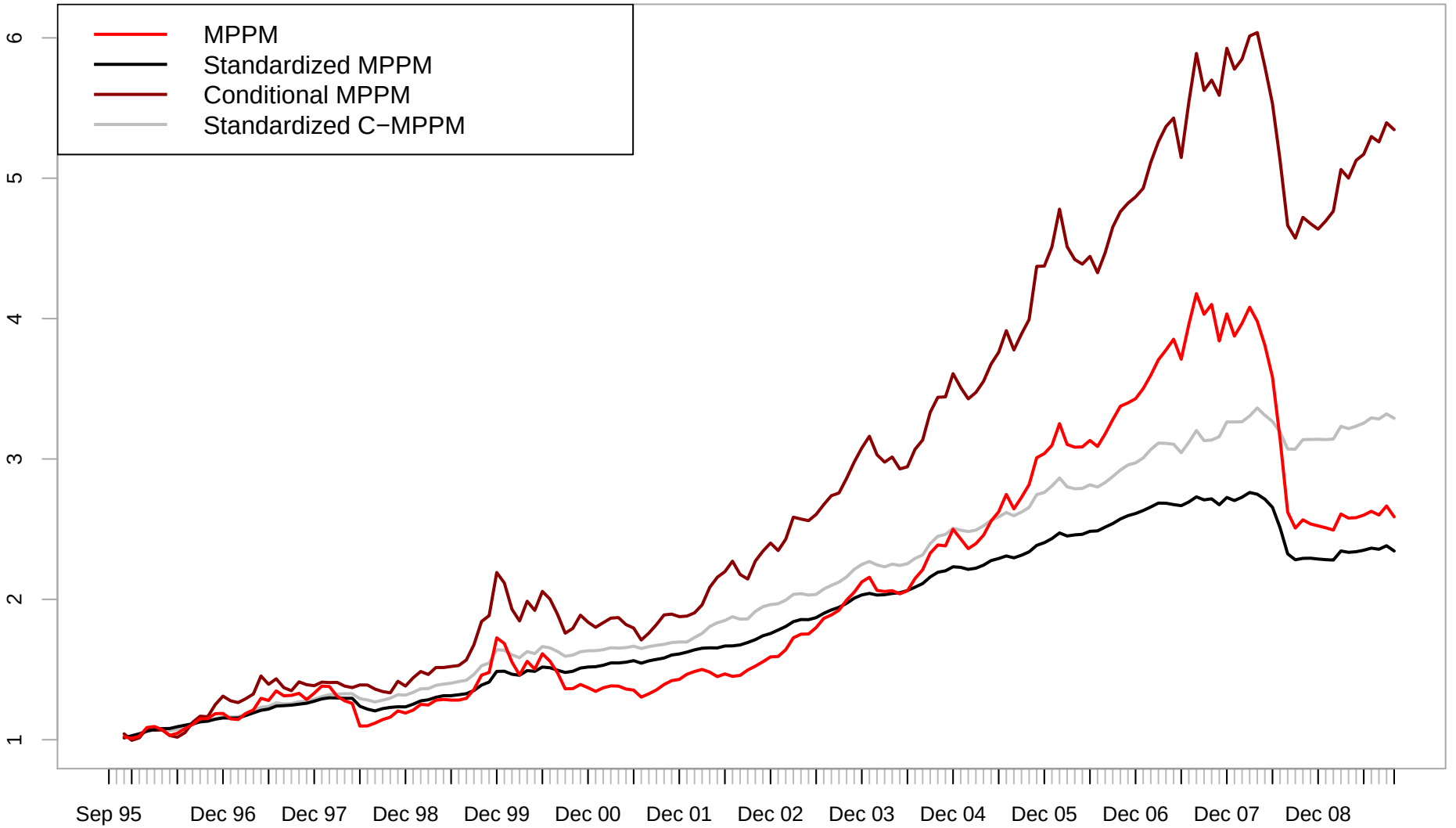

Figure 2 Panel A: Impact of fund size: Conditional MPPM portfolios

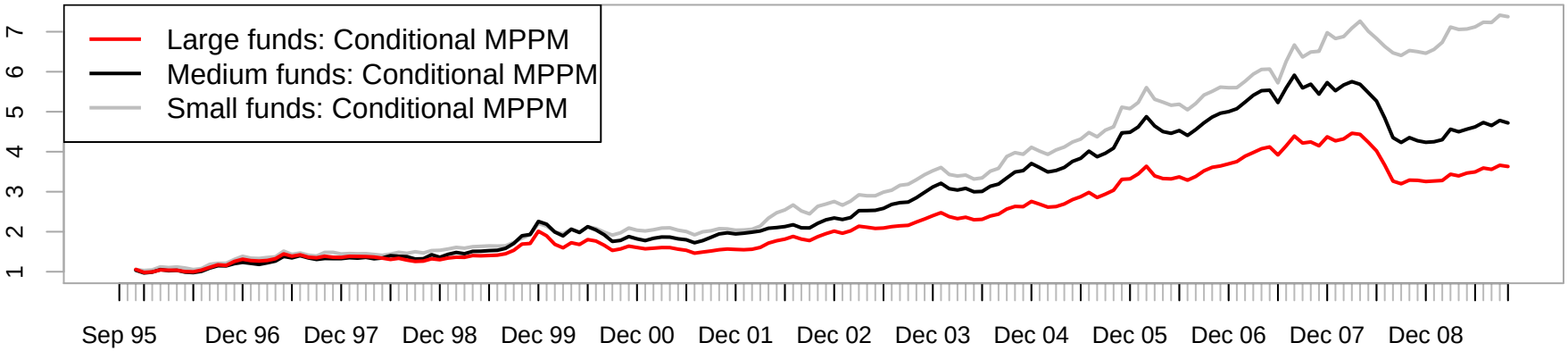

Figure 2 Panel B: Impact of fund size: Conditional standardized MPPM portfolios

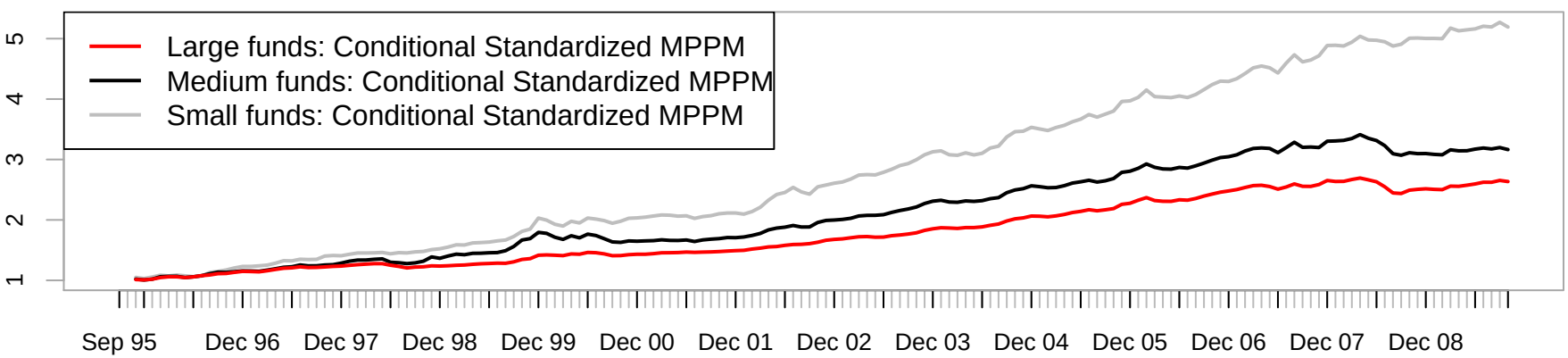

Figure 3 Panel A: Impact of share restrictions and rebalancing: Conditional MPPM portfolios

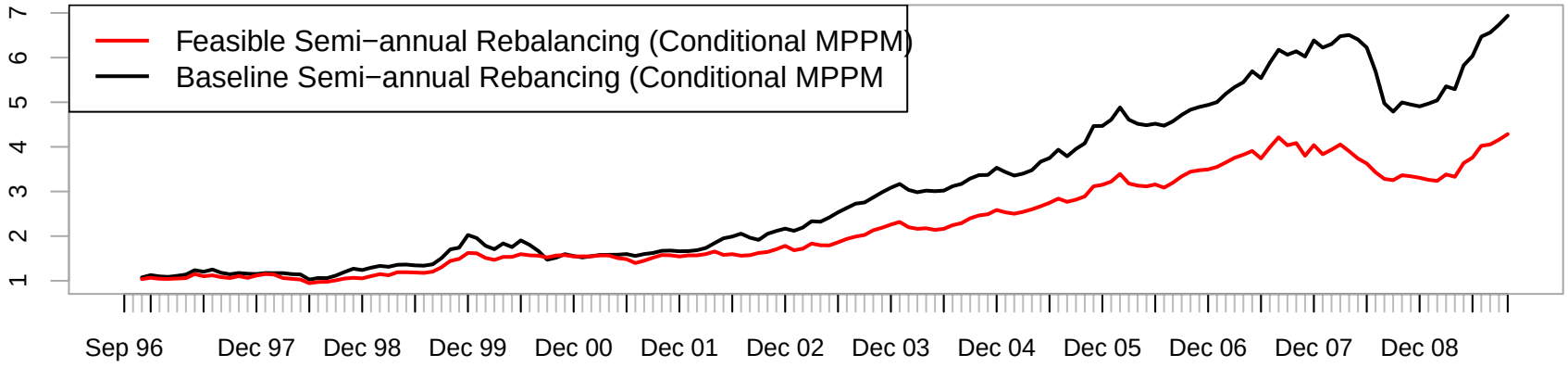

Figure 3 Panel A: Impact of share restrictions and rebalancing: Conditional Standardized MPPM portfol

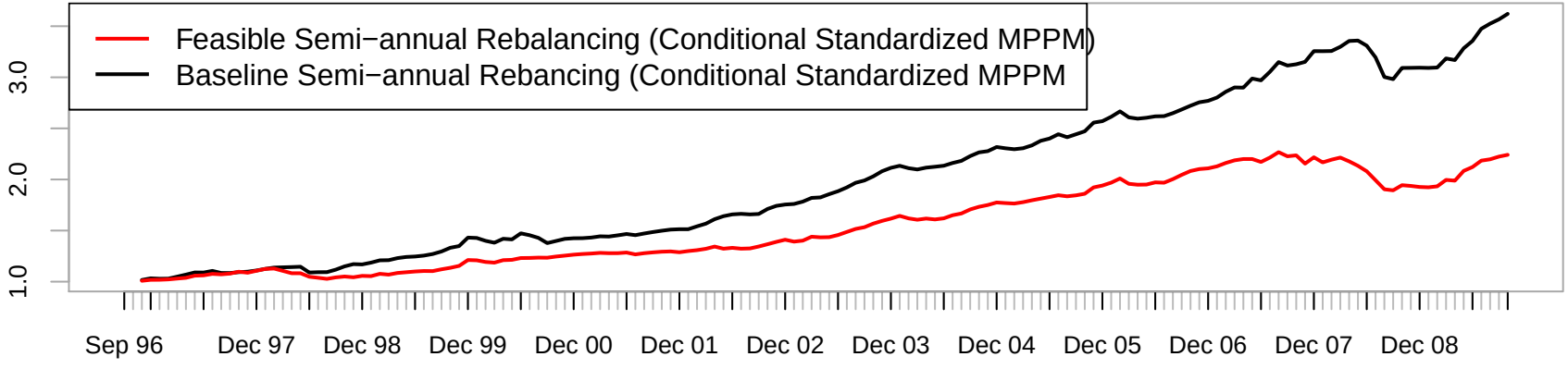

Table 1:Descriptive statistics for MPPMs

The Table presents the descriptive statistics for performance measures. MPPM is the manipulation-proof performance measure based on Goetzmann, Ingersoll, Spiegel, and Welch (2007) with a risk-aversion of 3. Stand. MPPM is the Standardized manipulation-proof performance measure defined as MPPM divided by its Standard error. C-MPPM is the conditional MPPM, while C-Stand-MPPM is the Standardized version of conditional MPPM. We use non-parametric kernel regression to estimate conditional MPPM measures with all the available return observations. As macro economic variables, we use term spread, default spread, volatility, dividend yield, TED spread and aggregate flow. t-stat of Alpha is defined using the Fung-Hsieh (2004) model, which uses as factors: S&P500 return minus risk-free rate, Wilshire small cap minus large cap return, excess return on the 10-year Treasury (BD10RET), the return spread of Moody's Baa minus 10-year Treasury, bond PTFS, currency PTFS, and commodities PTFS, where PTFS is primitive trend following strategy. Mean and Std are cross-sectional average and Standard deviation across respective performance measure. Corr is the rank correlation between performance measures.

			MPPM	Stand-MPPM	C-MPPM	C-Stand-MPPM	t-stat of alpha
	Mean	Std	Rank Correlation				
MPPM	2.48% pa	4.85	1.00	0.66	0.26	0.21	0.46
Stand-MPPM	0.85	1.78	0.66	1.00	0.21	0.44	0.78
C-MPPM	3.89% pa	3.34	0.26	0.21	1.00	0.61	0.17
C-Stand-MPPM	0.59	2.30	0.21	0.44	0.61	1.00	0.37
t-stat of alpha	0.80	1.51	0.46	0.78	0.17	0.37	1.00

Table 2: Persistence tests for sorts on unconditional MPPMs

Hedge funds are sorted on January 1 each year (from 1996 to 2010) into portfolios, based on their MPPM and standardized MPPM. We use the most recent 24 months of return observations preceding the evaluation period for the MPPM estimation. The portfolios are equally weighted monthly, so the weights are readjusted whenever a fund disappears. Funds with the highest past two-year MPPM or standardized MPPM comprise decile 10, and funds with the lowest comprise decile 1. MPPM is the manipulation-proof performance measure based on Goetzmann, Ingersoll, Spiegel, and Welch (2007) with risk-aversion of three. Stand. MPPM is the standardized manipulation-proof performance measure defined as MPPM divided by its standard error. ES is the monthly empirical expected shortfall at 95 percent level. Alpha, t-stat and IR are estimated using the Fung-Hsieh (2004) model, and they are defined as the annualized intercept of the regression model, t-statistic of intercept, and annualized intercept divided by the standard deviation of residual term. The factors of the augmented model are S&P 500 return minus risk-free rate, Wilshire small cap minus large cap return, excess return on the 10-year Treasury (BD10RET), the return spread of Moody's Baa minus 10-year Treasury, bond PTFS, currency PTFS, and commodities PTFS, where PTFS is primitive trend following strategy. Mean, Std and Sharpe are annualized mean return, standard deviation and Sharpe ratio of respective portfolio.

Panel A: Basic statistics for performance measures

Decile	MPPM	Stand. MPPM	ES	Alpha	t-stat	IR	Mean	Std	Sharpe
1	4.70	1.22	5.54	6.71	2.19	0.73	8.53	12.96	0.66
2	5.52	2.25	3.62	5.20	3.08	0.92	7.10	8.15	0.87
3	4.81	2.67	2.92	4.04	3.84	1.07	5.68	5.93	0.96
4	4.13	2.08	3.31	3.30	3.52	0.97	5.06	6.04	0.84
5	3.90	2.06	3.30	2.93	2.94	0.92	4.70	5.54	0.85
6	3.90	1.96	3.69	2.91	2.69	0.90	4.72	5.57	0.85
7	3.89	1.73	4.42	2.82	2.16	0.73	4.97	6.38	0.78
8	4.18	1.53	5.38	3.28	1.94	0.68	5.72	7.60	0.75
9	4.86	1.55	6.07	4.16	2.18	0.73	6.98	8.92	0.78
10	3.03	0.62	9.43	3.51	1.17	0.38	7.69	13.19	0.58
10-1	-1.67	-0.60	3.89	-3.20	-1.02	-0.35	-0.84	0.23	-0.08
t-stat	-0.38			-0.78		-0.88	-0.20		-0.26

Panel B: Hedge funds sorted on standardized MPPMs for proceeding 24 months

Decile	MPPM	Stand. MPPM	ES	Alpha	t-stat	IR	Mean	Std	Sharpe
1	2.47	0.87	4.40	3.12	1.43	0.48	4.40	9.02	0.49
2	5.65	2.15	3.87	5.67	3.06	0.96	7.55	8.90	0.85
3	6.16	2.57	3.93	5.65	3.99	1.08	7.76	8.07	0.96
4	5.31	1.99	4.60	4.87	3.72	1.03	7.10	8.44	0.84
5	3.69	1.31	5.16	2.78	1.92	0.56	5.53	8.46	0.65
6	4.85	1.72	5.37	3.93	2.62	0.80	6.70	8.42	0.80
7	3.53	1.24	5.52	2.57	1.71	0.55	5.27	8.07	0.65
8	3.45	1.19	5.67	2.50	1.46	0.51	5.11	7.82	0.65
9	4.07	1.41	5.61	3.07	1.68	0.60	5.66	7.67	0.74
10	5.64	3.25	3.25	4.78	3.68	1.46	6.20	4.49	1.38
10-1	3.17	2.38	-1.15	1.66	2.25	0.98	1.80	-4.53	0.89
t-stat	1.28			0.71		1.81	0.69		1.80

Table 3: Persistence tests for sorts on conditional MPPMs

Hedge funds are sorted on January 1 each year (from 1996 to 2010) into portfolios, based on their conditional MPPM and its standardized version. We use non-parametric kernel regression to estimate conditional MPPM measures with all the available return observations. As macro economic variables, we use term spread, default spread, volatility, dividend yield, TED spread and aggregate flow. The portfolios are equally weighted monthly, so the weights are readjusted whenever a fund disappears. Funds with the highest conditional MPPM comprise decile 10, and funds with the lowest comprise decile 1. *MPPM* is the manipulation-proof performance measure based on Goetzmann, Ingersoll, Spiegel, and Welch (2007) with risk-aversion of 3. *Stand. MPPM* is the standardized measure defined as the MPPM divided by its standard error. *ES* is the monthly empirical expected shortfall at 95 percent level. *Alpha*, *t-stat* and *IR* are estimated using the Fung-Hsieh (2004) model, and they are defined as the annualized intercept of the regression model, t-statistic of intercept, and annualized intercept divided by the standard deviation of residual term. *Mean*, *Std* and *Sharpe* are annualized mean return, standard deviation and Sharpe ratio of respective portfolio.

Panel A: Hedge funds sorted on conditional MPPMs

Decile	MPPM	Stand. MPPM	ES	Alpha	t-stat	IR	Mean	Std	Sharpe
1	-0.95	-0.20	8.92	0.45	0.17	0.05	3.67	13.60	0.27
2	1.87	0.57	6.29	1.50	0.94	0.29	4.01	9.09	0.44
3	2.36	0.92	4.73	1.45	1.21	0.39	3.65	7.05	0.52
4	2.84	1.23	4.55	1.74	1.52	0.53	3.89	6.33	0.61
5	4.19	2.21	3.32	3.24	3.62	1.11	4.95	5.43	0.91
6	4.53	2.82	2.87	3.66	4.28	1.20	5.17	4.98	1.04
7	5.95	3.41	3.09	4.94	5.16	1.48	6.77	5.63	1.20
8	5.81	2.87	3.54	4.97	4.08	1.22	6.85	6.34	1.08
9	6.72	2.57	4.86	5.99	3.87	1.14	8.51	8.33	1.02
10	8.65	2.32	6.65	9.80	3.23	0.95	12.87	13.09	0.98
10-1	9.61	2.52	-2.27	9.34	3.06	0.90	9.21	-0.51	0.71
t-stat	2.48			2.74		2.43	2.35		2.40

Panel B: Hedge funds sorted on standardized conditional MPPMs

Decile	MPPM	Stand. MPPM	ES	Alpha	t-stat	IR	Mean	Std	Sharpe
1	-1.49	-0.42	7.11	-1.34	-0.62	-0.20	1.02	9.91	0.10
2	2.52	0.82	5.74	2.15	1.37	0.45	4.46	8.67	0.51
3	2.49	0.91	4.97	1.93	1.54	0.45	4.16	8.09	0.51
4	4.01	1.43	5.17	3.31	2.44	0.76	5.76	8.24	0.70
5	4.83	1.79	4.98	4.00	3.39	0.95	6.57	8.24	0.80
6	5.45	2.28	4.16	4.67	3.91	1.07	6.98	7.79	0.90
7	5.43	2.19	4.40	4.45	3.52	1.01	6.93	7.66	0.90
8	5.64	2.22	4.33	4.76	3.03	0.91	7.16	7.73	0.93
9	7.24	3.16	4.15	6.56	3.79	1.23	8.58	7.19	1.19
10	8.05	5.69	2.39	7.22	5.89	1.91	8.65	4.69	1.84
10-1	9.55	6.11	-4.72	8.56	6.51	2.11	7.62	-5.22	1.74
t-stat	3.03			3.92		3.97	2.58		3.77

Table 4: Impact of hedge fund size on persistence tests based on MPPMs

Hedge funds are categorized on three groups based on fund size. Size groups are formed on a yearly basis in each December. Within size categories hedge are sorted on January 1 each year (from 1996 to 2010) into portfolios, based on their conditional MPPM and standardized conditional MPPM. We use non-parametric kernel regression to estimate conditional MPPMs with all the available return observations. As macro economic variables, we use term spread, default spread, volatility, dividend yield, TED spread and aggregate flow. The portfolios are equally-weighted monthly, so the weights are readjusted whenever a fund disappears. Funds with the highest MPPM comprise decile 10, and funds with the lowest comprise decile 1. *MPPM* is the manipulation-proof performance measure based on Goetzmann, Ingersoll, Spiegel, and Welch (2007). *Stand. MPPM* is standardized manipulation-proof performance measure defined as MPPM divided by its standard error. *ES* is the monthly empirical expected shortfall at 95 percent level. *Alpha*, *t-stat* and *IR* are estimated using the augmented Fung-Hsieh (2004) model, and they are defined as the annualized intercept of the regression model, t-statistic of intercept, and annualized intercept divided by the standard deviation of residual term. *Mean*, *Std* and *Sharpe* are annualized mean return, standard deviation and Sharpe ratio of respective portfolio.

Panel A: Hedge funds sorted on Conditional MPPMs

	Large hedge funds			Medium hedge funds			Small hedge funds		
Decile	MPPM	Stand. MPPM	ES	MPPM	Stand. MPPM	ES	MPPM	Stand. MPPM	ES
1	-3.25	-0.73	9.16	-0.89	-0.18	9.69	-1.36	-0.28	9.29
2	-0.64	-0.19	6.59	2.28	0.69	6.51	3.05	1.05	5.26
3	0.54	0.20	5.52	2.09	0.76	5.53	3.34	1.46	4.28
4	1.97	0.82	4.84	2.98	1.12	5.15	2.89	1.56	3.46
5	3.21	1.67	3.60	3.99	2.08	3.35	4.24	2.55	2.84
6	4.10	2.52	3.10	4.13	2.19	3.55	4.98	3.42	2.42
7	4.54	2.41	3.90	6.22	3.70	2.54	5.14	3.15	2.88
8	4.49	1.93	4.86	5.11	2.63	3.76	5.82	2.75	3.99
9	5.21	2.05	4.77	6.15	2.44	5.00	7.38	2.90	4.72
10	5.56	1.36	8.04	7.36	1.85	7.40	11.26	3.65	5.32
10-1	8.81	2.09	-1.12	8.25	2.03	-2.29	12.62	3.93	-3.97
t-stat	2.32			1.91			2.81		

	Large hedge funds			Medium hedge funds			Small hedge funds		
Decile	Alpha	t-stat	IR	Alpha	t-stat	IR	Alpha	t-stat	IR
1	-2.32	-0.99	-0.29	0.35	0.12	0.04	1.96	0.54	0.17
2	-1.09	-0.64	-0.21	1.82	1.20	0.36	3.52	1.74	0.52
3	-0.70	-0.52	-0.18	1.32	1.08	0.33	2.89	1.73	0.57
4	0.85	0.63	0.25	2.23	1.63	0.59	1.98	1.87	0.57
5	2.37	2.41	0.72	3.23	3.42	0.97	3.57	3.32	0.98
6	3.26	3.44	1.02	3.31	3.35	0.97	4.51	4.95	1.34
7	3.57	2.91	0.96	5.45	5.32	1.51	4.31	3.67	1.01
8	3.67	2.56	0.77	4.44	4.10	1.15	5.39	3.80	1.16
9	4.32	2.55	0.75	5.43	3.59	1.05	7.53	3.62	1.07
10	6.46	1.95	0.60	9.16	2.90	0.85	13.00	4.62	1.25
10-1	8.78	3.54	1.04	8.80	2.78	0.81	11.04	4.08	1.08
t-stat	2.60		2.41	2.29		1.87	2.88		2.91

	Large hedge funds			Medium hedge funds			Small hedge funds		
Decile	Mean	Std	Sharpe	Mean	Std	Sharpe	Mean	Std	Sharpe
1	0.81	12.47	0.07	3.87	13.71	0.28	4.86	16.05	0.30
2	1.38	8.71	0.16	4.56	9.44	0.48	5.30	9.61	0.55
3	1.92	7.20	0.27	3.66	7.82	0.47	4.58	7.06	0.65
4	3.00	6.17	0.49	4.29	7.04	0.61	3.75	5.84	0.64
5	3.97	5.40	0.74	4.83	5.75	0.84	4.96	5.35	0.93
6	4.68	4.73	0.99	4.97	5.73	0.87	5.63	5.04	1.12
7	5.38	5.63	0.95	7.04	5.68	1.24	6.06	6.08	1.00
8	5.74	6.87	0.84	6.14	6.32	0.97	7.07	7.03	1.01
9	6.94	8.27	0.84	7.91	8.29	0.95	9.56	9.35	1.02
10	10.16	13.60	0.75	12.07	13.81	0.87	15.14	12.66	1.20
10-1	9.35	1.13	0.68	8.21	0.10	0.59	10.27	-3.39	0.90
t-stat	2.48		2.27	1.91		2.05	2.23		2.81

Panel B: Hedge funds sorted on conditional standardized MPPMs

	Large hedge funds			Medium hedge funds			Small hedge funds		
Decile	MPPM	Stand. MPPM	ES	MPPM	Stand. MPPM	ES	MPPM	Stand. MPPM	ES
1	-1.43	-0.41	7.35	-1.34	-0.37	7.44	-3.41	-0.91	7.45
2	0.18	0.06	5.71	2.62	0.79	6.40	1.80	0.58	5.49
3	0.41	0.13	6.23	1.95	0.65	5.82	3.81	1.49	5.39
4	1.29	0.40	6.66	4.55	1.58	5.15	4.74	2.10	3.95
5	2.81	1.06	5.02	4.88	1.73	4.90	6.24	2.58	4.07
6	4.51	1.94	4.17	5.12	1.91	4.74	5.18	2.31	3.91
7	3.90	1.54	4.79	4.45	1.74	4.88	6.08	2.47	4.05
8	4.32	1.52	5.42	5.69	2.47	4.02	5.60	2.26	4.20
9	5.54	2.35	4.35	6.59	3.14	3.89	7.61	3.54	4.03
10	6.60	5.15	2.33	7.51	4.18	3.17	10.95	6.54	2.46
10-1	8.02	5.56	-5.02	8.85		4.55	14.36	7.45	-4.99
t-stat	2.70			2.66			3.71		

	Large hedge funds			Medium hedge funds			Small hedge funds		
Decile	Alpha	t-stat	IR	Alpha	t-stat	IR	Alpha	t-stat	IR
1	-1.44	-0.70	-0.23	-1.32	-0.62	-0.19	-2.29	-0.85	-0.27
2	-0.23	-0.17	-0.05	2.32	1.41	0.46	2.26	0.82	0.28
3	-0.10	-0.06	-0.02	1.52	1.05	0.32	3.82	2.14	0.63
4	0.64	0.38	0.13	4.12	3.17	0.90	4.41	3.11	0.85
5	1.69	1.34	0.37	4.27	3.49	0.99	6.04	3.64	1.13
6	3.46	2.67	0.76	4.60	3.43	0.95	4.66	3.40	0.93
7	2.66	1.82	0.59	3.69	2.89	0.79	6.31	3.61	1.06
8	3.27	1.71	0.55	4.95	3.35	0.98	5.28	3.06	0.88
9	4.70	2.53	0.89	5.90	4.20	1.25	7.73	3.97	1.17
10	5.77	5.30	1.82	6.90	4.30	1.39	10.66	6.78	1.96
10-1	7.20		2.05	8.22		1.59	12.95		2.24
t-stat	3.65		3.66	3.17		3.40	4.41		4.30

	Large hedge funds			Medium hedge funds			Small hedge funds		
Decile	Mean	Std	Sharpe	Mean	Std	Sharpe	Mean	Std	Sharpe
1	0.93	9.42	0.10	1.28	10.15	0.13	-0.28	11.11	-0.03
2	1.86	8.06	0.23	4.86	9.22	0.53	4.31	10.31	0.42
3	2.48	8.91	0.28	4.00	8.95	0.45	5.73	8.75	0.66
4	3.43	8.95	0.38	6.51	8.76	0.74	6.26	7.84	0.80
5	4.42	7.93	0.56	6.62	8.23	0.80	7.81	7.94	0.98
6	5.84	7.26	0.81	6.95	8.56	0.81	6.69	7.83	0.85
7	5.23	7.13	0.73	6.15	8.16	0.75	7.97	8.81	0.91
8	6.04	8.15	0.74	7.02	7.20	0.97	7.39	8.46	0.87
9	6.70	6.62	1.01	7.83	6.98	1.12	9.29	8.17	1.14
10	7.02	3.92	1.79	8.43	5.98	1.41	12.03	6.46	1.86
10-1	6.09		1.70	7.15		1.28	12.31		1.89
t-stat	2.21		3.30	2.24		3.27	3.41		4.03

Table 5: Impact of share restrictions and rebalancing horizons on persistence tests

Performance persistence tests based on a (i) semi-annual and (ii) annual rebalancing horizons. Within each rebalancing horizon decile porfolios are formed using only the feasible information taking into account fund-specifice share restrictions. For the feasible semi-annual (annual) rebalancing strategy, we exclude the funds with redemption and lockup periods longer that 6 (12) months. In addition, we exclude funds having notice periods longer than 3 months. This implies that we use 3 month lagged information to estimate MPPMs to mitigate look-ahead bias. We label the strategy to *feasible*, and compare its performance to baseline strategy's performance ignoring the share restrictions. The portfolios are equally-weighted monthly, so the weights are readjusted whenever a fund disappears. Funds with the highest MPPM comprise decile 10, and funds with the lowest comprise decile 1. *MPPM* is the manipulation-proof performance measure based on Goetzmann, Ingersoll, Spiegel, and Welch (2007). *Stand. MPPM* is the standardized manipulation-proof performance measure defined as MPPM divided by its standard error. *ES* is the monthly empirical expected shortfall at 95 percent level. *Alpha*, *t-stat* and *IR* are estimated using the Fung-Hsieh (2004) model, and they are defined as the annualized intercept of the regression model, t-statistic of intercept, and annualized intercept divided by the standard deviation of residual term. *Mean*, *Std* and *Sharpe* are the annualized mean return, standard deviation and Sharpe ratio of the respective portfolio.

Panel A: Hedge funds sorted on Conditional MPPMs

Feasible Semi-annual rebalancing taking into account share restrictions

Decile	MPPM	Stand. MPPM	ES	Alpha	t-stat	IR	Mean	Std	Sharpe
1	-1.99	-0.38	8.21	-0.63	-0.20	-0.07	2.74	13.49	0.20
2	2.27	0.82	4.78	1.92	1.04	0.34	3.96	8.25	0.48
3	2.55	1.12	3.99	1.70	1.23	0.39	3.67	6.66	0.55
4	3.06	1.48	3.78	1.99	1.62	0.54	3.94	5.82	0.68
5	3.43	1.90	3.03	2.33	2.18	0.73	4.10	5.09	0.81
6	3.87	2.08	3.25	2.77	2.50	0.83	4.59	5.25	0.87
7	4.93	2.78	3.11	3.91	3.96	1.12	5.72	5.54	1.03
8	5.64	2.72	3.88	4.62	3.67	1.09	6.73	6.51	1.03
9	5.88	2.30	4.72	5.13	3.19	0.93	7.60	8.23	0.92
10	8.37	2.33	6.43	8.95	3.26	0.98	12.12	12.21	0.99
10-1	10.37	2.71	-1.78	9.59	3.46	1.05	9.39	-1.28	0.79
t-stat	2.33			2.50		2.34	2.32		2.49

Baseline Semi-annual rebalancing

Decile	MPPM	Stand. MPPM	ES	Alpha	t-stat	IR	Mean	Std	Sharpe
1	-4.29	-0.92	9.04	-2.77	-1.04	-0.32	0.39	13.57	0.03
2	1.14	0.41	5.46	1.05	0.66	0.20	2.93	8.43	0.35
3	1.33	0.55	4.50	0.62	0.49	0.16	2.50	6.72	0.37
4	2.37	1.24	3.62	1.61	1.62	0.50	3.16	5.57	0.57
5	3.77	2.07	3.30	2.85	3.05	0.97	4.46	5.16	0.86
6	5.01	3.07	2.71	4.10	4.88	1.40	5.62	4.85	1.16
7	6.21	3.44	3.14	5.08	4.90	1.50	7.00	5.49	1.27
8	7.19	3.25	3.85	6.25	4.82	1.52	8.35	6.66	1.25
9	8.60	3.01	5.25	7.77	4.16	1.32	10.68	8.92	1.20
10	10.51	2.26	8.85	11.62	3.33	1.07	15.90	14.53	1.09
10-1	14.80	3.18	-0.19	14.39	4.37	1.39	15.51	0.96	1.06
t-stat	3.42			3.51		3.18	3.61		3.23

Feasible Annual rebalancing taking into account share restrictions

Decile	MPPM	Stand. MPPM	ES	Alpha	t-stat	IR	Mean	Std	Sharpe
1	3.25	0.81	6.30	5.78	2.01	0.69	7.19	12.94	0.56
2	4.43	1.66	4.09	4.60	2.75	0.92	6.02	8.12	0.74
3	4.16	1.82	3.70	3.95	2.89	0.97	5.29	6.70	0.79
4	4.29	2.15	3.21	3.41	3.39	1.00	5.11	5.71	0.90
5	4.24	2.14	3.29	3.24	3.16	1.06	5.01	5.43	0.92
6	3.75	1.91	3.55	2.75	2.36	0.83	4.51	5.41	0.83
7	4.38	1.89	4.77	3.31	2.31	0.85	5.44	6.29	0.87
8	4.86	2.02	4.54	3.97	2.54	0.87	6.13	6.97	0.88
9	3.11	0.97	6.28	2.65	1.27	0.44	5.25	9.04	0.58
10	0.81	0.15	10.32	1.93	0.53	0.19	5.82	13.42	0.43
10-1	-2.44	-0.66	4.02	-3.86	-1.48	-0.50	-1.37	0.48	-0.13
t-stat	-0.48			-0.85		-1.15	-0.29		-0.36

Baseline Annual rebalancing

Decile	MPPM	Stand. MPPM	ES	Alpha	t-stat	IR	Mean	Std	Sharpe
1	-0.95	-0.20	8.92	0.45	0.17	0.05	3.67	13.60	0.27
2	1.87	0.57	6.29	1.50	0.94	0.29	4.01	9.09	0.44
3	2.36	0.92	4.73	1.45	1.21	0.39	3.65	7.05	0.52
4	2.84	1.23	4.55	1.74	1.52	0.53	3.89	6.33	0.61
5	4.19	2.21	3.32	3.24	3.62	1.11	4.95	5.43	0.91
6	4.53	2.82	2.87	3.66	4.28	1.20	5.17	4.98	1.04
7	5.95	3.41	3.09	4.94	5.16	1.48	6.77	5.63	1.20
8	5.81	2.87	3.54	4.97	4.08	1.22	6.85	6.34	1.08
9	6.72	2.57	4.86	5.99	3.87	1.14	8.51	8.33	1.02
10	8.65	2.32	6.65	9.80	3.23	0.95	12.87	13.09	0.98
10-1	9.61	2.52	-2.27	9.34	3.06	0.90	9.21	-0.51	0.71
t-stat	2.48			2.74		2.43	2.35		2.40

Panel B: Hedge funds sorted on standardized conditional MPPMs

Feasible Semi-annual rebalancing taking share restrictions into account

Decile	MPPM	Stand. MPPM	ES	Alpha	t-stat	IR	Mean	Std	Sharpe
1	-0.96	-0.28	5.86	-1.29	-0.54	-0.20	0.94	8.39	0.11
2	0.52	0.18	5.23	0.21	0.11	0.04	2.22	8.11	0.27
3	2.88	1.04	4.90	2.44	1.47	0.45	4.67	8.48	0.55
4	4.24	1.63	4.50	3.36	2.21	0.66	5.83	7.97	0.73
5	5.28	2.01	4.32	4.51	3.12	0.95	6.85	7.84	0.87
6	5.41	2.13	4.29	4.41	3.26	0.99	6.95	7.78	0.89
7	5.64	2.35	4.38	4.70	3.20	0.98	7.11	7.60	0.94
8	5.97	2.52	4.22	5.24	3.32	1.04	7.44	7.62	0.98
9	5.26	2.40	4.12	4.28	2.76	0.84	6.53	7.01	0.93
10	5.87	3.53	3.11	4.74	4.31	1.28	6.52	4.98	1.31
10-1	6.83	3.81	-2.75	6.03	4.85	1.48	5.58	-3.41	1.20
t-stat	2.62			2.94		3.32	2.46		3.57

Baseline Semi-annual rebalancing

Decile	MPPM	Stand. MPPM	ES	Alpha	t-stat	IR	Mean	Std	Sharpe
1	-4.39	-1.24	6.70	-3.88	-1.76	-0.58	-1.92	9.72	-0.20
2	1.13	0.41	5.39	0.71	0.47	0.14	2.92	8.43	0.35
3	2.48	1.01	4.40	1.97	1.51	0.44	3.96	7.67	0.52
4	3.46	1.31	4.76	2.86	2.17	0.65	5.03	7.85	0.64
5	5.01	2.11	4.01	4.37	3.70	1.02	6.50	7.71	0.84
6	5.82	2.27	4.53	4.92	3.67	1.08	7.36	7.83	0.94
7	6.19	2.25	5.01	5.18	3.57	1.11	7.82	7.94	0.99
8	6.53	2.17	5.48	5.54	2.87	0.95	8.51	8.69	0.98
9	8.91	3.73	4.47	8.12	4.54	1.46	10.40	7.54	1.38
10	9.52	5.76	3.22	8.37	6.47	2.14	10.27	5.21	1.97
10-1	13.91	7.00	-3.48	12.26	8.23	2.72	12.19	-4.51	2.17
t-stat	4.66			5.32		4.37	4.36		4.14

Feasible Annual rebalancing taking share restrictions into account

Decile	MPPM	Stand. MPPM	ES	Alpha	t-stat	IR	Mean	Std	Sharpe
1	2.37	1.00	4.08	2.86	1.77	0.58	3.72	7.43	0.50
2	2.82	1.11	4.40	3.19	1.91	0.65	4.33	7.79	0.56
3	3.94	1.40	4.81	4.19	2.38	0.81	5.76	8.57	0.67
4	5.56	2.04	4.53	5.27	3.67	1.13	7.23	8.17	0.88
5	6.17	2.23	4.52	5.62	4.02	1.21	7.90	8.29	0.95
6	5.14	1.85	5.10	4.41	3.19	0.97	6.90	8.30	0.83
7	5.24	1.78	5.57	4.43	2.57	0.89	6.99	8.19	0.85
8	3.37	1.11	6.12	2.39	1.22	0.46	5.10	7.97	0.64
9	3.03	1.04	5.73	2.18	1.01	0.38	4.63	7.75	0.60
10	2.20	0.91	5.29	1.07	0.61	0.24	3.21	6.09	0.53
10-1	-0.17	-0.09	1.21	-1.79	-1.16	-0.34	-0.51	-1.34	0.03
t-stat	-0.07			-0.85		-0.81	-0.21		0.07

Baseline Annual rebalancing

Decile	MPPM	Stand. MPPM	ES	Alpha	t-stat	IR	Mean	Std	Sharpe
1	-1.49	-0.42	7.11	-1.34	-0.62	-0.20	1.02	9.91	0.10
2	2.52	0.82	5.74	2.15	1.37	0.45	4.46	8.67	0.51
3	2.49	0.91	4.97	1.93	1.54	0.45	4.16	8.09	0.51
4	4.01	1.43	5.17	3.31	2.44	0.76	5.76	8.24	0.70
5	4.83	1.79	4.98	4.00	3.39	0.95	6.57	8.24	0.80
6	5.45	2.28	4.16	4.67	3.91	1.07	6.98	7.79	0.90
7	5.43	2.19	4.40	4.45	3.52	1.01	6.93	7.66	0.90
8	5.64	2.22	4.33	4.76	3.03	0.91	7.16	7.73	0.93
9	7.24	3.16	4.15	6.56	3.79	1.23	8.58	7.19	1.19
10	8.05	5.69	2.39	7.22	5.89	1.91	8.65	4.69	1.84
10-1	9.55	6.11	-4.72	8.56	6.51	2.11	7.62	-5.22	1.74
t-stat	3.03			3.92		3.97	2.58		3.77

Table 6: Standard measures and performance persistence

The Table presents the performance persistence based on the standard measures: (i) t-statistic of Fung and Hsieh (2004) alpha, (ii) Fung and Hsieh (2004) alpha, (iii) Sharpe, and (iv) R-square of Fung and Hsieh (2004) model. Hedge funds are sorted on January 1 each year (from 1996 to 2010) into portfolios, based on the respective measures. We use the most recent 24 months of return observations preceding the evaluation period for the performance measure estimation. The portfolios are equally weighted monthly, so the weights are readjusted whenever a fund disappears. Funds with the highest performance measure comprise decile 10, and funds with the lowest comprise decile 1. *MPPM* is the manipulation-proof performance measure based on Goetzmann, Ingersoll, Spiegel, and Welch (2007). *Stand. MPPM* is the standardized manipulation-proof performance measure defined as MPPM measure divided by its standard error. ES is the monthly empirical expected shortfall at 95 percent level. *Alpha* , *t-stat* and *IR* are estimated using the Fung-Hsieh (2004) model, and they are defined as the annualized intercept of the regression model, t-statistic of intercept, and annualized intercept divided by the standard deviation of residual term. *Mean*, *Std* and *Sharp*e are the annualized mean return, standard deviation and Sharpe ratio of the respective portfolio.

Panel A: Hedge funds sorted on t-statistics of Fung and Hsieh (2004) alpha

Decile	MPPM	Stand. MPPM	ES	Alpha	t-stat	IR	Mean	Std	Sharpe
1	3.02	1.26	4.05	2.96	1.90	0.59	4.53	7.82	0.58
2	4.22	1.81	4.18	4.14	2.92	0.87	5.59	7.39	0.76
3	4.15	1.73	4.25	3.68	2.58	0.75	5.67	7.77	0.73
4	4.47	1.79	4.46	3.69	2.65	0.79	6.00	7.76	0.77
5	3.98	1.45	5.23	3.18	2.31	0.67	5.78	8.36	0.69
6	4.28	1.62	4.91	3.37	2.62	0.75	5.88	7.89	0.75
7	5.38	1.80	5.60	4.48	2.82	0.89	7.33	8.60	0.85
8	3.80	1.27	5.55	2.90	1.94	0.60	5.61	8.29	0.68
9	5.65	2.18	4.73	4.58	3.06	0.95	7.13	7.55	0.94
10	6.62	3.46	3.31	5.48	5.00	1.53	7.39	5.39	1.37
10-1	3.59	2.20	-0.74	2.51	3.10	0.94	2.85	-2.43	0.79
t-stat	2.09			1.63		2.46	1.65		2.37

Panel B: Hedge funds sorted on Fung and Hsieh (2004) alphas

Decile	MPPM	Stand. MPPM	ES	Alpha	t-stat	IR	Mean	Std	Sharpe
1	4.10	1.29	5.24	5.30	2.30	0.72	6.86	10.70	0.64
2	3.79	1.88	3.67	3.22	2.61	0.75	4.91	6.69	0.73
3	3.55	1.84	3.48	3.04	2.61	0.80	4.47	5.98	0.75
4	3.75	1.93	3.77	2.73	2.69	0.84	4.63	5.80	0.80
5	3.66	1.80	3.73	2.68	2.51	0.86	4.50	5.62	0.80
6	3.98	1.85	4.05	2.86	2.68	0.89	4.94	6.00	0.82
7	4.71	2.03	4.38	3.65	3.05	1.01	5.82	6.45	0.90
8	5.05	1.94	5.00	4.12	3.05	0.89	6.62	7.80	0.85
9	5.62	1.79	5.91	4.67	2.70	0.79	7.99	9.66	0.83
10	5.82	1.32	7.92	6.23	2.52	0.71	10.15	13.00	0.78
10-1	1.72	-19.68	-13.08	0.94	0.22	-0.01	3.30	2.30	0.14
t-stat	0.58			0.36		-0.05	1.19		0.59

Panel C: Hedge funds sorted on Sharpe ratios

Decile	MPPM	Stand. MPPM	ES	Alpha	t-stat	IR	Mean	Std	Sharpe
1	1.87	0.79	3.53	1.64	0.95	0.32	3.05	7.04	0.43
2	5.20	2.03	3.96	5.43	2.98	0.93	6.93	8.47	0.82
3	5.35	2.41	3.55	4.92	3.52	1.02	6.73	7.47	0.90
4	5.96	2.43	4.08	5.48	3.98	1.09	7.62	8.19	0.93
5	4.73	1.61	5.22	4.10	2.86	0.82	6.73	8.81	0.76
6	4.36	1.51	5.60	3.48	2.33	0.69	6.31	8.70	0.73
7	4.59	1.62	5.53	3.71	2.52	0.76	6.44	8.40	0.77
8	3.36	1.08	6.09	2.51	1.36	0.47	5.34	8.58	0.62
9	3.82	1.17	6.33	3.00	1.48	0.53	5.77	8.48	0.68
10	5.43	2.87	3.63	4.50	3.28	1.22	6.14	5.12	1.20
10-1	3.57	2.08	0.10	2.86	2.33	0.90	3.09	-1.92	0.77
t-stat	1.66			1.37		1.79	1.39		1.83

Panel D: Hedge funds sorted on R-squares of Fung and Hsieh (2004) model

Decile	MPPM	Stand. MPPM	ES	Alpha	t-stat	IR	Mean	Std	Sharpe
1	3.23	0.91	6.91	3.64	3.37	0.97	6.40	11.20	0.57
2	5.51	1.92	5.02	5.32	4.05	1.12	7.76	9.52	0.82
3	6.13	2.28	4.46	5.60	4.22	1.15	7.97	8.57	0.93
4	5.18	1.80	4.70	4.82	2.94	0.91	7.07	8.60	0.82
5	5.37	1.87	5.02	4.69	2.92	0.92	7.12	8.22	0.87
6	3.33	1.25	5.17	2.18	1.34	0.45	4.80	7.50	0.64
7	3.98	1.59	4.79	2.91	1.79	0.60	5.29	7.06	0.75
8	4.37	2.06	3.81	3.31	2.29	0.77	5.33	6.01	0.89
9	3.48	1.71	4.09	2.31	1.65	0.59	4.36	5.77	0.75
10	4.20	2.70	2.96	3.45	2.82	1.02	4.70	4.30	1.09
10-1	0.97	1.79	-3.95	-0.19	-0.55	0.05	-1.71	-6.90	0.52
t-stat	0.36			-0.15		0.14	-0.62		1.42