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Abstract

We seek evidence that top performing hedge funds follow a different strategy than mediocre performing hedge funds by examining the structure of significant risk factors that explain the out of sample excess net returns. Consequently, we examine the out of sample returns of hedge funds to determine, first, if hedge funds have outperformed the market in recent years, second, whether top funds actually outperform mediocre performing hedge funds and thirdly, whether top funds have a different risk profile than mediocre hedge funds and therefore appear to follow a different strategy. We find that the risk profile of top quintile performing funds is distinctly different than mediocre quintile funds by having fewer risk factors that appear to anticipate the troubling economic conditions that prevailed after 2006.

***JEL* classification:** G11, G12, G23

Keywords: Hedge funds; Manipulation proof performance measure; hedge fund strategies; stochastic dominance, bootstrap.

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http://faculty.chicagobooth.edu/lubos.pastor/research/

I. Introduction

The hedge fund industry continues to attract enormous sums of money. For example, BarclayHedge, a hedge fund information provider, reports that the global hedge fund industry has nearly $2.5 trillion of assets under management as of December 2014, a 13% increase from the previous year.[2] Yet, due to the comparatively light regulatory nature of the industry, we know very little about how these assets are managed or what strategies hedge fund managers pursue.

We seek evidence that top performing hedge funds follow a different strategy than mediocre performing hedge funds by examining the structure of significant risk factors that explain the out of sample excess net returns. Consequently, we examine the out of sample returns of hedge funds to determine, first, if hedge funds have outperformed the market in recent years, second, whether top funds actually outperform mediocre performing hedge funds and thirdly, whether top funds have a different risk profile than mediocre hedge funds and therefore appear to follow a different strategy.

We enhance our investigation by using robust non-parametric techniques. Specifically, we employ stochastic dominance tests to determine if the hedge fund industry outperformed the market in recent years and whether top performing funds persistently outperform mediocre performing hedge funds. As explained more formally later, in portfolio decision making the principle of stochastic dominance is superior to the commonly used mean-variance rule since it has the advantage of exploiting the information embedded in the entire distribution of stock market returns instead of a finite set of moments of the distribution**.** Another attractive feature of stochastic dominance is that being a non-parametric analysis, statistical inference based on stochastic dominance tests does not depend on any asset pricing model or require hedge fund returns to be normally distributed.

We also employ quantile regressions to investigate the strategies executed by top and mediocre performing funds. Unlike normal regression techniques, quantile regressions provide the risk profile of hedge fund returns. Specifically, quantile regressions examine the quantile response of the excess hedge fund return at say the 25th quantile, as the values of the independent variables change. Quantile regressions do this for all quantiles, or in other words, the whole distribution of the dependent variable, thereby providing a much richer set of information concerning how the excess return of hedge funds response to different sources of systematic risk. To comprehend this huge amount of information, we graph the response by quantile of the excess hedge fund return to changes in the systematic risk factors. Finally, we examine how the risk profile of top and mediocre performing funds change through time by running rolling quantile regressions throughout our sample period from January 2001 to December 2012. This allows us to determine how the risk profile of top and mediocre performing hedge funds respond as the generally robust economic conditions turn sour post 2006.

[2] http://www.barclayhedge.com/

This area of research complements the recent literature that seeks to understand the factors that influence hedge fund performance and performance persistence. Specifically, Li, Zhang and Zhao (2011) examine the effects of managerial characteristics, Sun, Wang and Zheng (2012) examine strategy distinctiveness, Cumming et al. (2012) examine the influence of regulation, Chincarini (2014) compares the effect of quantitative and qualitative investment styles and Schaub and Schmid (2013) study the effects of liquidity restrictions on hedge fund performance and performance persistence. Our contribution is to examine whether top performing funds are in some sense "different" from the run of the mill hedge funds and whether this difference can be attributed to a distinctive risk profile that mediocre hedge funds are unable or unwilling to emulate.

This paper raises several questions. Is there any evidence that the hedge fund industry, as an asset class, has outperformed "the market" in the recent past that includes the recessionary and slow growth economic conditions that have evolved post 2006? Can the recently developed manipulation proof performance measure of Goetzmann et al. (2007) provide evidence that top performing hedge funds persistently deliver top performance? If so, for how long? Do top funds follow a distinctive strategy, as indicated by a distinctly different risk profile, that lead to persistent, superior performance? How did the hedge fund industry react to the liquidity lead crash and subsequent recovery?

We investigate these questions using diversified portfolios of fund of fund and of all hedge funds. For each month, we form portfolios of hedge funds by quintile according to that month's manipulation proof performance measure of Goetzmann et al. (2007) and by the traditional Sharpe ratio. Unlike the Sharpe ratio, the manipulation proof performance measure is robust to the return distribution and is resistant to manipulation by portfolio managers. We then hold these portfolios for twenty four months and then measure the out of sample performance of these portfolios by quintile and by performance measure. Therefore, we examine the out of sample performance of diversified portfolios so that our evidence mimics the activities of investors in hedge funds.

Accordingly, our empirical investigation proceeds in four stages. First, we examine whether all hedge funds have indeed outperformed "the market" in recent years. We find that all hedge funds, as approximated by all fund of funds and by all hedge funds, do second order stochastically dominate "the market" in the January 2001 to December 2012 time period but only if we define the market as the Russell 2000 index. For more narrow benchmarks, the S&P500 and the MSCI emerging market indices, the hedge fund asset class dominates the market only according to the heavily criticized Sharpe ratio. In contrast, the more robust manipulation proof performance measure (hereafter MPPM) finds that the hedge fund industry does not stochastically dominate the market when compared to the S&P500 and the MSCI indices. This result is consistent with Bali, Brown and Demirras (2012) who also find that the TASS fund of fund hedge funds do not outperform the S&P 500 in recent years.

Second, we examine whether top performing hedge funds still persistently outperform mediocre performing hedge funds out of sample once we include the challenging economic conditions of recent years using the traditional Sharpe ratio as well as the Goetzmann et al. (2007) manipulation proof performance measure. We find that the top performing quintile of hedge funds do second order stochastically dominate the mediocre performing third quintile out of sample according to the MPPM. However, this superior performance persists for only six months, far less than the two or three years reported earlier by Boyson (2008) and Ammann, Huber and Schmit (2013) who use less robust parametric techniques.

Third, we examine the role liquidity as well as other risk factors, such as momentum, plays in achieving excess net rates of return. We do this for funds of superior and mediocre performance in an attempt to determine whether or not top performing funds follow a distinctive strategy, or take on a distinctively different risk profile, than mediocre performing funds. We find that top performing fund returns are driven by a different risk profile than is evident in more modestly performing funds. Specifically, top performing fund returns are exposed to a market and a momentum factor whereas mediocre third quintile fund returns are driven by additional factors for liquidity and momentum reversal. In detail, quantile regressions reveals that the market and momentum factors are statistically significant in explaining top fund of fund returns six months out of sample at the 25th, 50th and 75th quantiles. In contrast, mediocre third quintile fund of fund returns are significantly related to the market, momentum, liquidity and momentum reversal factors six months out of sample at the 50th and 25th quantiles. At the 75th quantile however, mediocre third quintile performing funds look like top performing funds in that the returns are significantly related only to a market and a momentum factor.

Finally, we explore the strategies followed by top and mediocre performing fund of fund hedge funds by examining the time series values of the coefficients for risk factors by quantile as we move from the robust economic conditions that prevailed prior to 2007 to the recessionary and slow growth conditions that have evolved since. We find that for the top performing funds, the dispersion of coefficient values for the market return factor and for the momentum factor increase as the upper and lower bounds for these coefficients increase in the months leading up to the financial crisis period but by 2008 the coefficient values return to a more normal range. A similar pattern for the market return and momentum factors is evident for the mediocre third quintile performing funds. However, for third quintile performing funds, large increases for the upper and large decreases for the lower bounds for the long term reversal and liquidity factors is delayed until the actual recession of 2008. This pattern of the coefficients hints that the market and the momentum factors, factors that are significant in explaining top fund performance, anticipate the liquidity crisis and subsequent recession. In contrast, the long term reversal and aggregate liquidity factors, factors that significantly explain mediocre hedge fund performance, merely react to the 2008 recession. These results are consistent with Stivers and Sun (2010) who find that the momentum factor is procyclical and with Kacperczyk et al. (2014) who find evidence that market timing is a task rather than an innate talent that top performing managers can execute.

In the next section we review the literature. Section II reports some related literature while Section III describes the data. Our empirical analysis proceeds in Section IV and V while Section VI summarizes and concludes.

II. Literature review

The case for hedge funds "beating" the market is not clear. While Ackermann et al. (1999) find evidence that hedge funds outperform mutual funds they are unable to find any evidence that hedge funds outperform market indices. Meanwhile, Brown et al. (1999) find that Sharpe ratios and Jensen's alphas of hedge fund portfolios are higher than for the S&P 500. However, Brown et al. (1999) express concern that survival bias could have exaggerated the performance of hedge funds. Weighing up all of the evidence, Stultz (2007) concludes that hedge funds offer returns commensurate with risk once hedge fund manager compensation is accounted for. More recently, Dichev and Yu (2011) document a sharp reduction in buy and hold returns for a very large sample of hedge funds and CTAs, from on average 18.7% for 1980 to 1994, to 9.5% from 1995 to 2008. As discussed later in detail, our more recent sample, from January 31, 2001 to December 31, 2012, reports that hedge fund returns are even lower, obtaining only 37 basis points per month (4.5% per year) net rate of return on average. Moreover, Bali, Brown and Demirras (2012) find that only the long short equity hedge and emerging market hedge fund indices outperformed the S&P500 in recent years**.** Clearly, it is possible that the hedge fund industry is entering a mature phase and prior conclusions concerning the performance of the hedge fund industry may no longer apply.

Some research strongly supports persistence, other research is more equivocal. Ammann et al. (2013) and Boyson (2008) find that top performing hedge funds formed on Fung and Hsieh (2004) alphas continue to provide statistically significant performance three and two years later respectively. Ammann et al. (2013) find that strategy distinctiveness as suggested by Sun, Wang and Zheng (2012) is the strongest predictor of performance persistence while Boyson (2008) finds that persistence is particularly strong amongst small and relatively young funds with a track record of delivering alpha. Fung et al. (2008) find that funds of hedge funds with statistically significant alpha are more likely to continue to deliver positive alpha.

More critically, Kosowski et al. (2007) find evidence that top funds deliver statistically significant out of sample performance when funds are sorted by the information ratio, but not when the funds are sorted by Fung and Hsieh (2004) alphas. Capocci, Corhay and Hübner (2005) find that only funds with prior mediocre alpha performance continue to deliver mediocre alphas in both bull and bear markets. In contrast, past top deliverers of alphas continue to deliver positive alphas only during bullish market conditions. More recently, Brandon and Wang (2013) find that superior performance for equity type hedge funds largely disappears once liquidity is accounted for and Slavutskaya (2013) finds that only alpha sorted bottom performing funds persist in producing lower returns in the out of sample period. Finally, Hentati-Kaffel and Peretti (2015) find that nearly 80% of all hedge fund returns are random where evidence of performance persistence is concentrated in hedge funds that follow event driven and relative value strategies.

Another strand of the hedge fund literature heavily criticizes the use of common performance measures such as the Sharpe ratio, alpha and information ratio. Amin and Kat (2003) question the use of these measures as they assume normally distributed returns and/or linear relations with market risk factors. This strand of research inspired proposals for a wide variety of alternative performance measures purporting to resolve issues of measuring performance in the face of non-normal returns. However, Eling and Shoemaker (2007) find that the ranking of hedge funds by the Sharpe ratio is virtually identical to twelve alternative performance measures. Goetzmann's et al. (2007) point out that common performance measures such as the Sharp ratio, alpha and information ratio can be subject to manipulation, deliberate or otherwise. These issues imply that the use of these performance measures can obtain misleading conclusions. Goetzmann et al. (2007) then go on to develop the manipulation proof performance measure MPPM, so called because this performance measure is resistant to manipulation.

A final strand of the literature examines the structure of risk factors that explains hedge fund returns. Sadka (2010) demonstrates that liquidity risk is an important factor that explains the cross section of hedge fund returns. Meanwhile, Billio, Getmansky and Pelizzon (2009) find that when volatility is high, hedge funds have significant exposure to liquidity risk and Boyson, Stahel and Stulz (2010) find evidence of hedge fund contagion that they attribute to liquidity shocks. More recently, Bali, Brown and Caglayan (2014) show that a substantial proportion of the variation in hedge fund returns can be explained by several macroeconomic risk factors. However, we do not know much about how top performing hedge funds add value when compared to mediocre performing hedge funds.

III. Data

The data we use comes from a variety of sources. We use Credit Suisse/Tremont Advisory Shareholder Services (TASS) database for the hedge fund data. We collect the Fama French risk factors from the French Data library and the aggregate liquidity factor from the Lubos Pastor Data library. Finally, equity index information is from DataStream.

We select all US dollar hedge funds that have three years of historical performance prior to our start date of January 31, 2001. We need to have three years of data to avoid multi-period sampling bias. Hedge fund managers often need 36 months of return data before investing in a hedge fund so including funds with a shorter history can be misleading for these investors (See Bali, Brown and Caglayan 2014, online appendix 1). We continue to collect all US dollar hedge funds with three years of data up to December 31, 2012 as that is the last update of the TASS data that we have.[3] When we examine the number of observations in the TASS database, we note the exponential growth of the data that seems to have moderated from January 1998 onwards as from that date, the total number of fund year observations grew from 20,000, peaking at 50,000 in 2007 and falling to approximately 29,000 in 2012.[4] By commencing our study from January 1998 we avoid a possible growth trend in the data.

From this database, we collect all monthly holding period returns net of fees. We adjust for survivorship bias by including all funds both live and dead. We also adjust for backfill bias by including data on a given fund only from the date that the fund was listed in TASS. We estimate the Sharpe ratio as the monthly holding period return of the hedge fund less the one month T-bill return (as reported in the French Data Library) divided by the standard deviation of excess returns calculated over the previous two years.

We calculate the manipulation proof performance measure of Goetzmann et al. (2007) as reported below

$$MPPM\,(A) \equiv \left[\frac{1}{(1-A)\Delta t} \ln\left(\frac{1}{T} \sum_{t=1}^{T} \left[(1+r_t)/(1+r_{ft})^{(1-A)} \right] \right) \right]$$

where $t = 1, \ldots, T$ and A is the risk aversion parameter, r_t is the monthly holding period return of the hedge fund, r_{ft} is the one month t-bill return, and Δt is one month. The measure MPPM(A) represents the certainty equivalent excess (over the risk free rate) monthly return for an investor with a risk aversion of A employing a utility function similar to the power utility function. This implies that MPPM is relevant for risk adverse investors who have constant relative risk aversion. The MPPM does not rely on any distributional assumptions. We estimate MPPM(A) over the previous two years using a risk aversion parameter A of 2 and then 3.[5]

Table 1 reports some characteristics of our data that consists of 4,600 funds with 176,483 fund month observations. This sample is smaller than Bali, Brown and Demirras (2012) who include non US dollar denominated funds but is comparable in size to Ammann et al. (2013) and Hentati-Kaffel

[3] Our understanding is that there are no Madoff funds in the December 31, 2012 version of the TASS database that we use. We are aware than six feeder funds heavily invested in the Madoff Funds, specifically Fairfield Sentry Ltd (FFS), Kingate Global Fund Ltd (KING), Optimal Strategic US Equity Ltd (OPTI), SantaClara I Fund (SANTA), LuxAlpha Sicav - American Selection (LUX) and Herald Fund SPC - USA Segregated Portfolio One (HRLD). We checked the live and dead TASS database by fund name, and close variations of these names, and find that none of these funds are in the database. We conclude that the Madoff incident does not directly affect our results.

[4] In contrast, the number of fund month observations nearly tripled in the previous five years. The details of the annual fund month observations are available from the corresponding author upon request.

[5] Goetzmann et al. (2007) suggest that the market believes the risk aversion varies between 2 and 4. We experimented with a variety of risk aversion parameters from 1 through 10 finding that the rankings by Θ did not change very much. We chose 2 and 3 to illustrate the robustness of our results as hedge fund investors should be more risk tolerant that most investors.

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and Peretti (2015). A striking fact is the huge attrition rate of hedge funds, less than one half of all of the hedge funds included in our data are live at the end of our sample period. Live funds are larger, have a longer history and have better performance than dead funds. Moreover, net hedge fund returns are modest, only 37 basis points per month (approximately 4.5% annually) on average throughout the sample period. This confirms the continuing decline in hedge fund returns reported by Dichev and Yu (2011).

<<Tables 1, 2 and 3 about here>>

We also examine the time series characteristics of our data in Table 2. Clearly, the hedge fund industry is accident prone, with overall negative excess rates of return in 2002, 2008 and 2011. For each of these disappointing years, the number of funds in our sample decreases either during the year (2002) or in the year following (2008, 2011). The manipulation proof performance measure gives an even more critical assessment of the performance of hedge funds, revealing that hedge funds were unable to return a certainty equivalent premium above the risk free rate for five of the twelve years in our sample. Overtime, the average size and age of hedge funds is increasing although there is a noticeable decrease in the average size post 2008.

We chose not to break out our results by investment style because the number of funds for each style will vary excessively year by year throughout our sample period. Instead we will aggregate our data by fund of funds, the largest grouping of hedge funds by style with 1,273 funds and 45,700 fund month observations and by all hedge funds. Fung and Hsieh (2008) suggest that fund of fund hedge fund data is more reliable than other aggregations of hedge fund data as fund of fund data is less prone to reporting biases and so are more reflective of the actual losses and investment constraints faced by investors in hedge funds.

We form equally weighted portfolios of all fund of fund and all hedge funds monthly from January 31, 2001 until December 31, 2012 from the above data. The distribution of monthly average returns, Sharpe and MPPM performance measures for our sample period and for our hedge funds and the benchmark S&P 500, Russell 2000 and MSCI emerging market indices are reported in Table 3. It is clear that all performance measures for all assets have significant departures from normality so it is imperative that we conduct our empirical investigation using techniques that are robust to the empirical return distribution of performance measures.

IV. Stochastic dominance tests for hedge funds performance

In this section we develop a procedure for comparing distributions of hedge funds returns. We are interested in testing whether hedge funds outperform the market, or whether top performing funds outperform mediocre funds out of sample. Our procedure for testing differences between distribution functions relies on the concept of first and second order stochastic dominance. Stochastic dominance analysis provides a utility-based framework for evaluating investors' prospects under uncertainty, therefore facilitating the decision making process. With respect to the traditional mean-variance analysis, stochastic dominance requires less restrictive assumptions about investor preferences. Specifically, stochastic dominance does not require a full parametric specification of investor preferences, but relies only on the non-satiation assumption in the case of first order stochastic dominance and risk aversion in the case of second order stochastic dominance (see Appendix A for a formal definition of first and second order stochastic dominance criteria). If there is stochastic dominance, then the expected utility of an investor is always higher under the dominant asset than under the dominated asset. This implies that the dominated asset would not be chosen by any non-satiated investor.

Testing for stochastic dominance can be based on comparing (functions of) the cumulate distributions of the hedge funds and stock market indexes. Of course, the true cumulated distribution functions are not known in practice. Therefore, stochastic dominance relies on the empirical distribution functions. In the literature several procedures have been proposed to test for stochastic dominance. An early work by McFadden (1989) proposed a generalization of the Kolmogorov-Smirnov test of first and second order stochastic dominance among a number of prospects (distributions) based on i.i.d. observations and independent prospects. Later works by Klecan et al. (1991) and Barrett and Donald (2003) extended these tests allowing for dependence in observations, and replacing independence with a general exchangeability amongst the competing prospects. An important breakthrough in this literature is given in Linton, Maasoumi and Whang (2005) where consistent critical values for testing stochastic dominance are obtained for serially dependent observations. The procedure also accommodates for general dependence amongst the prospects which are to be ranked. Since hedge fund returns are well known to have fat-tail distributions, the inference procedure suggested by Linton et al. (2005) will be adopted in our work.

A: Testing for Hedge Fund Performance

In order to test if the returns of portfolios of all fund of fund and all hedge funds outperform the market we consider the three performance measures as represented by the Sharpe ratio, MPP2 and MPP3. For each portfolio, we test to determine if the returns of the portfolio first or second order stochastically three market indexes, namely, the Russell 2000, S&P 500 and the MSCI emerging market indexes.

The essence of our test strategy is as follows. For a given portfolio, let X_i (for $i = 1, \dots, 3$) be the performance measure of the portfolio and let Y_j denote the efficiently priced asset represented by the stock market index j (for $j = 1, \ldots, 3$). Let s be the order of stochastic dominance. To establish the direction of stochastic dominance between X_i and Y_j we test the following hypotheses

$$H_0^1 : X_i \succ_s Y_j,$$

and

$$H_0^2 : Y_j \succ_s X_i,$$

with the alternative the negation of the null hypothesis for both H_0^1 and $H_{0.}^2$ We infer that returns of the portfolio stochastically dominate the returns from the market if we accept H_0^1 and reject H_0^2. Conversely, we infer that the market returns stochastically dominate the portfolio returns if H_0^2 hypothesis cannot be rejected. In cases where neither of the null hypotheses can be rejected we infer that the stochastic dominance test is inconclusive. Details of the stochastic dominance testing procedure are given in Appendix A.

Panels A, B and C in Table 4 report the results of this stochastic dominance test. For each panel, columns three and four report the empirical p-values for the first and second order stochastic dominance tests. Under the null hypothesis if $H_0^1 : X_1 \succ_s Y_j$ the fund of fund portfolio stochastically dominates the *j* market index at *s* order, whereas under $H_0^2 : Y_j \succ_s X_1$ the opposite is true. The *p*-values in Table 4 were obtained using the bootstrap algorithm described in Appendix A with a 1000 bootstrap replications. Similarly, columns five and six report the *p*-values of the test that relate the portfolio X_2 which represents the overall of US dollar hedge funds.

<<Table 4 about here>>

In Table 4, rejection of the null hypothesis is based on small *p*-values of the test statistic described in Appendix A. Coming to the result of the test statistic, in Table 4 for all stock market indexes, the hull hypothesis of first order stochastic dominance is always rejected no matter which performance measure is taken into consideration. This result is not surprising as first order stochastic dominance implies that all-non-satiated investors will prefer portfolio X_i regardless of whether they are risk neutral, risk-averse or risk loving. Therefore, first order stochastic dominance criterion may be too stringent.

Panel A in Table 4 clearly shows that by any performance measure and for either aggregation of hedge fund portfolios, the hedge fund industry second order dominates the stock market as represented by the Russell 2000. Specifically, we see that the hypothesis $H_0^1 : X_i \succ_{s:=2} Y_j$ cannot be rejected no matter which performance measure we take into consideration.

The test results are however different in Panel B and C. For the S&P500 and the MSCI, neither of the null hypothesis $H_0^1: X_i \succ_{s:=2} Y_j$ or $H_0^2: Y_j \succ_{s:=2} X_i$ can be rejected. Therefore, the stochastic dominance test is inconclusive for both MPPM2 and MPPM3 performance measures. This result is consistent with Bali, Brown and Demirras (2012) who also find that the fund of fund hedge fund strategy does not outperform the S&P500 in recent years according to the MPPM. In contrast, the hedge fund industry second order dominates the stock market according to the Sharpe ratio. Noting that the Sharpe ratio is by construction sensitive to departures from normality of monthly hedge fund returns, we rely on the more robust MPPM to conclude that the hedge fund industry second order stochastically dominates the market only when we approximate the market by the broader Russell 2000 index.

B: Performance persistence of top performing hedge funds

We now consider whether top performing funds outperform mediocre funds out of sample. Our testing strategy is to construct top (fifth) quintile portfolios formed on the Sharpe ratio, the MPPM(2) and MPPM(3) performance measures and compare the performance of these portfolios to the performance of similarly formed mediocre (third) quintile portfolios.[6] These quintile portfolios are based on the average performance over the previous two years and each portfolio, once formed, is held for twenty-four months. Given our twelve year sample period, from January 31, 2001 to December 31, 2012, we form 120 monthly portfolios for each quintile. The portfolios are equally weighted. Individual funds that were included in the formation portfolio that later disappeared during the out of sample twenty-four month valuation period are assumed reinvested in the remaining funds. Therefore, we measure persistence of performance by comparing the out of sample performance of portfolios formed on the top and mediocre portfolio according to a given performance measure for up to twenty four months after the quintile portfolios were formed.

The testing strategy is as follows. Let $\delta = t + \varepsilon$ be the time increment, for each j, let Z_k be the *k-th* quintile of Θ, where $\Theta = \{Z_k : z_k | \delta,\ Z_k \subseteq X_i, k \in \{1, \dots, 5\}\}$. We consider the subset $\widetilde{\Theta} \subseteq \Theta$ with $k \in \{3,5\}$ then, for each i, j and δ, we test the following hypotheses

[6] We chose to compare the fifth and third quintile portfolios rather than the fifth and first quintile because it is clear that the first quintile is tainted by survivorship bias. To investigate, we form portfolios by quintile according to the net holding period return, average the 120 holding period returns for each of the 24 out of sample months and then plot the monthly net holding period return by quintile and by out of sample month. While the average holding period returns for the fifth and third quintiles asymptotically decline towards zero from above, the first quintile asymptotically decline towards zero from below. Moreover, there is a much larger attrition of funds in the first than in the fifth or third quintiles indicating that the improvement in the performance of the first quintile is merely the attrition of poorly performing funds. Consequently, we suspect that the performance of the first quintile is tainted by survivorship bias and so forms a suspect benchmark for determining performance persistence. The results of this analysis are available from the corresponding author upon request.

$$H_0^1: Z_5 \succ_s Z_3,$$

and

$$H_0^2: Z_3 \succ_s Z_5.$$

As before, the alternatives are the negation of the null hypotheses. We infer that returns of the top portfolio Z_1 stochastically dominate the returns from the market if we accept H_0^1 and reject H_0^2. Conversely, we infer that the returns of the mediocre portfolio Z_2 stochastically dominate the portfolio returns if H_0^2 hypothesis cannot be rejected.

Table 5 reports the results of our performance persistence tests. Table 5 is organized into three panels, each panel reporting whether the portfolio formed by top funds stochastically dominate the portfolio formed by mediocre funds one, six, twelve, eighteen and twenty-four months out of sample according to the Sharpe ratio, the MMPM(2) and MPPM(3) respectively. For each panel, reading along the columns, columns three and four reports the *p*-values of the first and second order stochastic dominance test for top versus mediocre funds and the reverse for the fund of funds strategy and the last two columns reports the same for the all hedge funds in our sample.

<<Table 5 about here>>

Looking at X_2, for the heavily criticized Sharpe ratio, the portfolio of top hedge funds Z_5 first and second order stochastically dominate mediocre hedge funds portfolio Z_3 up to twenty-four months out of sample for all hedge funds. This result is in line with much of the literature, including Amman et al. (2013) and Boyson (2008). For the fund of funds portfolio X_1 however, Z_5 first order dominate the portfolio formed with mediocre performing hedge funds Z_3 for only one month and second order dominate for six months out of sample according to the Sharpe ratio.

The results for the fund of fund portfolio X_1 seem more believable than those relating to the total fund portfolio X_2 as first order dominance is a very strong claim and the claim that first order dominance holds for as long as two years appears extreme. Moreover, a reliance on the fund of fund rather than all funds is consistent with Fung and Hsieh (2008) suggestion that fund of fund hedge fund data is more reliable than other aggregations of hedge fund data.

It is striking that the conclusions we obtain differ according to which performance statistic is considered. In contrast to when measuring performance using the Sharpe ratio, we find that the corresponding dominance tests when using the MPPM(2) and MPPM(3) performance measures are consistent for the overall sample of funds and for the fund of fund sub-sample. Specifically, top quintile funds first and second order dominate mediocre funds up to six months out of sample. Unlike

Slavutskaya (2013), we do find some evidence of performance persistence for top funds, but the persistence is much more modest than found by Ammann et al. (2013) and Boyson (2008). We conclude that the top performance of hedge funds do persist, but for only for a few months rather than a few years.

V. Risk profile of hedge funds

Table 5 shows that top quintile performing hedge funds continue to out-perform the corresponding mediocre hedge funds at least six months out of sample. This suggests that top performing funds are different in some way that enables them achieve distinctly superior performance. In an attempt to discover how these top performing funds are different from mediocre funds we examine the risk profiles of top and mediocre funds six months out of sample.

Following the traditional literature, we use the Fama and French (1995) empirical asset pricing model as the basic multi-factor model that describes market risks that hedge fund managers take in order to generate returns. We augment this model for momentum (Carhart 1997), momentum reversal and aggregate liquidity (Pastor and Stambaugh 2003) as prior research suggests that these are likely to be other priced risk factors.

In this section we restrict our attention to the fund of fund portfolio X_1 and explain out of sample net excess returns of hedge funds by quintile for the fund of fund sector as our results above suggest that the aggregation of hedge funds by the fund of fund strategy obtains more reliable results and because Fung and Hsieh (2008) suggest that fund of fund hedge fund data is more reliable than other aggregations of hedge fund data. The procedure is to regress excess hedge fund returns for the quintiles of hedge funds at six months out of sample on risk factors for the excess market return MKTRF, for the Fama and French (1995) risk factors for size SMB and value HML, the Carhart (1997) risk factor for momentum MOM, for momentum reversal LTR and for the Pastor and Stambaugh (2003) liquidity factor AGGLIQ.

In detail, let $\ddot{\Theta}$ be the subset $\ddot{\Theta} \subseteq \Theta$ with $\ddot{\Theta} = \left\{Z_k : z_k \middle| \delta,\ Z_k \subseteq X_1, k \in \{3,5\}\right\}$. We define

$$F_k = Z_k - RF,$$

where Z_k are the monthly rate of returns of the portfolio X_1 for six months after the portfolio was formed and *RF* is the one month rate of return from the French Data Library. Then, the model specified is as follows:

$$F_k = f(MKTRF, SMB, HML, \text{MOM}, LTR,\ AGGLIQ). \qquad (1)$$

We estimate equation (1) using the quantile regression method. Quantile regression is a procedure for estimating a functional relationship between the response variable and the explanatory variables for all portions of the probability distribution. The previous literature focused on estimating the effects of the above risk factors on the conditional mean of the excess returns. However, the focus on the conditional mean of returns may hide important features of the hedge fund risk profile. It is natural to go beyond central location of the return distribution. While the traditional linear regression model can address the question of whether or not the risk factor in equation (1) affects the hedge fund conditional returns, it can't answer another important question: Does a one unit increase of the risk factor of equation (1) affects low risk hedge fund returns differently from high risk fund returns? Therefore, the conditional mean function represents well the center of the distribution but little information is known about the rest of the distribution. In this respect, the quantile regression estimates provide information regarding the impact of risk factors at all parts of the returns' distribution.

Equation (1) can be specified as

$$Q(\tau|R = r) = R'\beta(\tau), \qquad \text{for } 0 \leq \tau \leq 1 \qquad (2)$$

where $Q(\cdot) = \inf\{f_k : G(F_k) \geq \tau\}$ and $G(F_k)$ is the cumulate density function of F_k. The vector R_t is the set of risk factors in equation (1) and β is a vector of coefficients to be estimated. In equation (2) the τ-quantile is expressed as the solution of the optimization problem

$$\hat{\beta}\,(\tau) = argmin \textstyle\sum_{i=1}^{n} \rho_\tau(F_k - R'\beta) \qquad (3)$$

where $\rho_\tau(\xi) = \xi\big(\tau - I(\xi < 0)\big)$ and $I(\cdot)$ is an indicator function. Equation (3) is then solved by linear programming methods and the partial derivative:

$$\hat{\beta} = \frac{\partial Q(\tau|R = r)}{\partial r}$$

can be interpreted as the marginal change relative to the τ-quantile of $Q(\cdot)$ due to a unit increase in a given element of the vector R. As τ increases continuously from 0 to 1, it is possible to trace the entire distribution of F_k conditional on R.

Table 6 reports our quantile regression estimates of equation (2) for the top and mediocre portfolios of net returns six months out of sample. In column three the estimated coefficients for equation (2) with dependent variable the quantiles of F_5 are reported, whereas column five relates to the estimates of equation (2) with the quantiles of F_3 as response variable. In column four and six the bootstrapped standard errors of the estimated coefficient are reported. The standard errors were calculated by resampling the estimated residuals of equation (2) using the non-parametric bootstrap method with a 1000 replications.

In Table 6 the results are reported at the 25th, 50th and 75th quantiles. This enables us to delve within the distribution of the top performing and mediocre portfolios to see if the risk profile for the less performing funds differs from higher performing funds within a given performance quintile. This provides a much richer set of results rather than merely considering the conditional mean of F_k as a function of the risk factors in equation (1).

<<Table 6 about here>>

Clearly, top performing hedge funds have a distinctly different risk profile than mediocre funds. Top performing funds have a statistically significant market risk and momentum factor at all three quantiles. In contrast, mediocre quantile funds also have a statistically significant liquidity and momentum reversal factor at the 25th and 50th quantiles. This clearly suggests that mediocre funds rely on illiquid assets to achieve performance whereas this is not a significant factor for top performing funds. Moreover, the momentum reversal factor is significantly negative implying that mediocre funds “give up” some of the earlier momentum profits. This is in accordance with the theory proposed by Vayanos and Woolley (2013) who model momentum and momentum reversal as a consequence of gradual order flows in response to shocks in investment returns. This suggests that mediocre funds do not quickly change their strategy when it starts to fail. Interestingly, the risk profile of mediocre funds at the 75th percentile is the same as top performing funds. This suggests that the very best of the mediocre performing hedge funds emulate top performing hedge funds.[7]

Figure 1 and 2 provide a graphical view of the marginal effects of risk factors on excess returns. Figure 1 and 2 correspond to the estimates in Table 6, but the estimates are reported this time for each τ, with $0 \leq \tau \leq 1$. The bold line in Figure 1 shows the return response for the risk factors for top performing funds, six months out of sample and Figure 2 shows the same for mediocre performing funds. The thinner lines provide the 5% upper and 95% lower bootstrap envelope.

<<Figures 1 and 2 about here>>

The graphical patterns in Figure 1 and 2 show the effect of a covariate on the response variables F_k. For example, in Figure 1 the fifth box shows the marginal effect on the conditional distribution of F_5 due to a one additional unit of risk factor MOM fixing the other risk factors. Figure 1 shows that

[7] We replicate table 6 using all hedge fund data despite the warnings of Fung and Hsieh (2008) that fund of fund data is more reflective of the actual losses and investment constrains faced by hedge funds. Even so, the results we obtain are similar to those reported above except that top performing hedge fund returns are inversely related to the market factor at all quintiles. These results are available from the corresponding author upon request.

the MOM effect for top funds is significantly positive at all but the very lowest quantiles because the confidence envelope does not cross the zero line so that zero is outside the confidence interval. Figure 1 also shows an upward-sloping curve for the effect of momentum for all quantiles less than the 0.20th quantile. The increase decelerates above the 0.20th quantile.

Looking at Figure 2, we see that for mediocre performing funds, LTR is significantly different from zero for all τ (the quantile on the x-axis) and increases with τ. This can be interpreted as a location shift and shape shift. If there was only a location shift, increasing the risk factor LRT would cause every quantile to increase by the same amount, leading to a graph of the estimated coefficient versus τ resembling a horizontal line. Instead the estimated coefficient for LTR is monotonically increasing with τ , that is $\beta^{(\tau)} > \beta^{(\varrho)}$ for $\tau > \varrho$. This property tells us that an additional unit of LTR has a greater effect on F_3 for higher risk quantile hedge funds than for lower F_3 brackets.[8]

Finally, we estimate the time varying coefficients for equation (2). This will allow us to investigate the evolution of the estimated coefficients over time and so investigate how the risk profile of hedge funds adjust as we approach and move through the 2007-08 financial crisis. In order to avoid clutter, we focus on the conditional median equation (i.e. the 50th quantile) in (2). In this case the parameters in equation (2) are a function of time and the model can be written as

$$Q(\tau|R=r) = \beta_{0t} + \beta_{1,t}MKTRF + \beta_{2,t}SMB + \beta_{3,t}HML + \beta_{4,t}MOM + \beta_{5,t}LTR + \beta_{6,t}AGGLIQ + \varepsilon. \qquad (4)$$

We examine how the risk profiles of top and mediocre hedge funds change over time by running rolling quantile regressions. Figures 3 and 4 plot the estimates of the coefficients of (4) using a 36 month constant size window. Figure 3 reports the results for top quintile funds together with the 95 confidence envelope and Figure 4 reports the same for mediocre hedge funds. Both figures show that the confidence envelope of the market risk and the momentum factors rise in 2006 and early 2007 suggesting that these risk factors were subject to greater uncertainty in the run up to the recent financial crisis. These results are consistent with Stivers and Sun (2010) who find that the momentum factor is procyclical. Meanwhile, the liquidity and momentum reversal factors appear to have a delayed response to the financial crisis for mediocre hedge funds as the confidence envelope of these coefficients rise after the early part of 2007. Together, these finding suggest that top performing hedge funds have a risk profile that anticipates growing economic risks whereas mediocre hedge funds have a risk profile that includes factors that react rather than anticipate growing economic uncertainty.

[8] It is worth noticing that the proposed estimation method is robust to heteroskedastic innovation in (4). It is well known that return data have quite heavy tails. Most of the available literature uses ordinary least squares methods with Newey West correction to provide an estimate of the covariance matrix of the parameters for the standard errors. However, even when the Newey West correction is used the estimated parameters are sensitive to outliers. The quantile regression is able overcome this problem.

These results are consistent with Kacperczyk et al. (2014) who find that market timing is a task that only skilled managers can perform.

<<Figures 3 and 4 about here>>

VI. Conclusions

In response to the questions raised in the introduction, our stochastic dominance tests find that only when compared to the broad Russell 2000 index do hedge funds outperform the market. Unlike Capocci, Corhay and Hübner (2005) and Slavutskaya (2013), we find that the superior performance of top quintile hedge funds do persist according to the MPPM, but only for six months rather than for two or three years as reported by Ammann et al. (2013) and Boyson (2008). We find evidence that that top funds follow a distinctive strategy that mediocre performing hedge funds are unable or unwilling to emulate.

Specifically, we investigate whether the risk profile of hedge funds differ by quintile by performing a quantile regression on out of sample net returns on an augmented Fama and French (1995) and Carhart (1997) asset pricing model that includes the Pastor and Stambaugh (1997) liquidity risk factor. We find that the risk profile of top quintile performing funds is distinctly different than mediocre quintile funds by having fewer risk factors that appear to anticipate the troubling economic conditions that prevailed after 2006. In more detail, the out of sample excess returns of top quintile funds are positively associated with market risk and with momentum at the 25th, 50th and 75th quantiles. However, excess returns for mediocre performing funds at the 25th and 50th quantiles are, in addition to market risk and momentum factors, significantly associated with two other factors, liquidity and momentum reversal, that appear to react to the difficult economic conditions that evolved after 2006. The positive association with liquidity suggests that at least some of the returns from investment in these funds are merely premiums from holding illiquid assets. Moreover, there is a significant inverse association with momentum reversal, suggesting that some of the returns earned from momentum are lost as these funds are slow to change a losing strategy. Interestingly, the excess returns on mediocre funds at the 75th quintile have the same risk profile at top quintile funds suggesting that, potentially, there are some funds within the mediocre performing funds that are emulating the strategies of top performing funds.

We conclude that persistently superior performing hedge funds are likely following a different strategy than mediocre performing funds as they have a distinctly different risk profile. Evidently, top performing funds avoid relying on passive investment in illiquid investments and avoid losses from momentum reversal but earn risk premiums by accepting market risk and following strategies that return momentum profits.

Appendix A

The theory of stochastic dominance offers a method of decision making by ranking distribution of random variables under given conditions of the utility function of the decision makers. In portfolio decision making, the principle of stochastic dominance is vastly more efficient than the commonly used mean-variance rule since it has the advantage of exploiting the information embedded in the entire distribution of stock market returns instead of a finite set of statistics. Below, we first briefly define the criteria of stochastic dominance and we then describe the testing procedure for stochastic dominance adopted in the paper.

Concept of stochastic dominance

Let U_1 denote the class of all von Neumann-Morgestern type of utility functions, u, such that $u' \geq 0$, also let U_2 denote the class of all utility functions in U_1 for which $u'' \leq 0$, and U_3 denote a subset of U_j for which $u''' \leq 0$. Let X_1 be and X_2 denote be two random variables and let $F_1(x)$ and $F_2(x)$ be the cumulative distribution functions of X_1 and X_2 respectively, then we define

Definition 1. X first order stochastically dominates Y if and only if either:

i) $E[u(X_1)] \geq E[u(X_2)]$ for all $u \in U_1$
ii) $F_1(x) \leq F_2(x)$ for every x with strict inequality for some x.

According to Definition 1 investors prefer hedge funds with higher returns to lower returns, which imply that a utility function has a non-negative first derivative. First order stochastic dominance is a very strong result, for it implies that all non-satiated investors will prefer X_1 to X_2, regardless of whether they are risk neutral, risk-averse or risk loving. Second order stochastically dominance also takes risk aversion into account, but it posits a negative second derivative (which implies diminishing marginal utility) of the investor's utility function. This is sufficient for risk aversion. More formally, the definition of second order stochastic dominance is as follows:

Definition 2. X_1 second order stochastic dominates X_2 if and only if either:

i) $E[u(X_1)] \geq E[u(X_2)]$
ii) $\int_{-\infty}^{x} F_1(t)dt \leq \int_{-\infty}^{y} F_2(t)dt$ for every x with strict inequality for some x.

Testing procedure for stochastic dominance

The test of first order and second order stochastic dominance are based on empirical evaluations of the conditions in above definitions. Let $s = 1,2$ represents the order of stochastic dominance. Let $\Phi \in \{$ the joint support of X_i and X_j, for $i \neq j\}$. Let $D_i^s(x)$ and $D_j^s(y)$ the empirical distribution of X_i and X_j, respectively. To test the null hypothesis, $H_0 : X_i \gtrsim_s X_j$ (where "$\gtrsim_s$" indicates stochastic dominance at the s order), we test that

$$H_0 : D_i^s(x; F_i) \leq D_j^s(x; F_j),$$

$\forall\, x \in \mathbb{R}, s = 1,2$. The alternative hypothesis is the negation of the null, that is

$$H_1 : D_i^s(x; F_i) > D_j^s(x; F_j),$$

$\forall\, x \in \mathbb{R}, s = 1,2$. To construct the inference procedure we consider the Kolmogorov-Smirnov distance between functionals of the empirical distribution functions of X_i and X_j and define the test statistic as

$$\widehat{\Lambda} = \min \sup_{x \in \mathbb{R}} \sqrt{N} \left[\widehat{D}_i^s\left(x; \widehat{F}_i\right) - \widehat{D}_j^s\left(x; \widehat{F}_j\right) \right], \qquad (1A)$$

where $t = 1, \ldots, N$ and

$$\widehat{D}_i^s\left(x; \widehat{F}_i\right) = \frac{1}{N(s-1)!} \sum_{t=1}^{T} 1\left(X_{i,t} \leq x\right)(x - X_{i.t})^{s-1}, \qquad (2A)$$

and $\widehat{D}_j^s(x; \widehat{F}_j)$ is similarly defined. Linton *et al*. (2005) show that under suitable regularity conditions $\widehat{\Lambda}$ converges to a functional of a Gaussian process. However, the asymptotic null distribution of $\widehat{\Lambda}$ depends on the unknown population distributions, therefore in order to estimate the asymptotic *p*-values of the test we use the overlapping moving block bootstrap method. The bootstrap procedure involves calculating the test statistics $\widehat{\Lambda}$ using the original sample and then generating the subsamples by sampling the overlapping data blocks. Once that the bootstrap subsample is obtained, one can calculate the bootstrap analogue of $\widehat{\Lambda}$. In particular, let *B* be the number of bootstrap replications and *b* the size of the block. The bootstrap procedure involves calculating the test statistics $\widehat{\Lambda}$ in (1A) using the original sample and then generating the subsamples by sampling the $N - b + 1$ overlapping data blocks. Once that the bootstrap subsample is obtained one can calculate the bootstrap analogue of $\widehat{\Lambda}$. Defining the bootstrap analogue of (1A) as

$$\hat{\Lambda}^{*}=\min \sup_{x\in\mathbb{R}}\sqrt{N}\left[\hat{D}_i^{s*}\left(x;\hat{F}_i\right)-\hat{D}_j^{s*}\left(x;\hat{F}_j\right)\right] \qquad (3A)$$

where

$$\hat{D}^{*}\left(x,\hat{F}_k\right)=\frac{1}{N(s-1)!}\sum_{i=1}^{N}\{1(X_{2i}^{*}\leq x)(x-X_{2i}^{*})^{s-1}-\omega(i,b,N)1(X_{2i}^{*}\leq x)(x-X_{2i}^{*})^{s-1}\}$$

and

$$\omega(i,b,N)=\begin{cases} i/b & if \ \in[1,b-1] \\ 1 & if\ i\in[1,N-b+1] \\ (N-i+1)/b & if\ [N-b+2,N] \end{cases}$$

The estimated bootstrap p-value function is defined as the quantity

$$p^{*}\left(\hat{\Lambda}\right)=\frac{1}{N-b+1}\sum_{i=1}^{N-b+1}1\left(\Lambda^{*}\geq\hat{\Lambda}\right).$$

Under the assumption that the stochastic processes X_i and X_j are strictly stationary and α-mixing with $\alpha(j)=O(j^{-\delta})$, for some $\delta>1$, when $B\to\infty$ the expression in (3A) converges to (1A). Also, asymptotic theory requires that $b\to\infty$ and $b/N\to 0$ as $N\to\infty$.

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Table 1: Sample of Hedge Funds.

The table reports the basic sample statistics and the performance of hedge funds from January 31, 2001 until December 31, 2012. Statistics are compiled only from the date that they were listed in the TASS database. All returns are in percent. SR is the Sharpe ratio. MPPM(2) and MPPM(3) are manipulation proof performance measures of Goetzmann et al. (2007) with a risk aversion parameter of 2 and 3 respectively.

Strategy	*Number*	*Assets*	*Age*	*Rf*	*RoR*	*SR*	*MPPM(2)*	*MPPM(3)*
Convertible Arbitrage	124	$251.47	6.44	0.18	0.32	0.45	0.00	-0.02
Dedicated Short Bias	24	$25.73	6.05	0.17	-0.08	-0.06	-0.06	-0.07
Emerging Markets	417	$196.34	5.94	0.10	0.59	0.18	0.01	-0.01
Equity Market Neutral	182	$170.66	5.79	0.15	0.36	0.25	-0.02	-0.04
Event Driven	347	$375.06	6.67	0.15	0.48	0.30	0.03	0.02
Fixed Income Arbitrage	114	$302.15	6.29	0.17	0.37	0.69	0.02	0.01
Fund of Funds	1273	$206.00	5.97	0.12	0.12	0.10	-0.01	-0.02
Global Macro	158	$550.54	5.89	0.13	0.42	-1.03	0.03	0.02
Long/Short Equity Hedge	1265	$155.44	6.27	0.14	0.44	0.10	0.01	0.00
Managed Futures	295	$257.77	6.43	0.12	0.56	0.26	0.01	-0.01
Multi-Strategy	266	$437.17	5.86	0.12	0.43	0.23	0.02	0.01
Options Strategy	12	$92.53	7.70	0.13	0.55	0.48	0.03	0.02
Other	123	$273.05	5.74	0.11	0.60	0.41	0.03	0.02
Grand Total	4600	$238.48	6.14	0.13	0.37	0.15	0.01	0.00
Live Funds	1922	$256.67	6.27	0.08	0.45	0.20	0.02	0.01
Dead Funds	2678	$221.24	5.62	0.18	0.30	0.09	0.00	-0.01
First Half	2033	$223.80	5.17	0.23	0.74	0.22	0.04	0.03
Second Half	2567	$246.31	6.32	0.08	0.19	0.11	-0.01	-0.02

Assets are in millions, age is in years, returns are in percent per month and returns are net of fees

Table 2: Time Series Characteristics of the Sample of Hedge Funds.
The table reports the time series statistics of the performance of hedge funds from January 31, 2001 until December 31, 2012. Statistics are compiled only from the date that they were listed in the TASS database. All returns are in percent. SR is the Sharpe ratio. MPPM(2) and MPPM(3) are the manipulation proof performance measures of Goetzmann et al. (2007) for investors with a risk aversion parameter of 2 and 3 respectively.

Year	*Number*	*Assets*	*Age*	*Rf*	*RoR*	*SR*	*MPPM(2)*	*MPPM(3)*
2001	512	$147.72	4.42	0.31	0.25	0.13	-0.08	-0.10
2002	151	$156.68	4.80	0.13	-0.11	0.08	-0.02	-0.03
2003	246	$171.35	5.32	0.08	1.39	0.61	0.05	0.04
2004	455	$223.09	5.09	0.10	0.80	0.44	0.08	0.07
2005	333	$253.57	5.15	0.25	0.71	0.29	0.04	0.03
2006	336	$271.30	5.57	0.39	0.93	0.36	0.06	0.06
2007	397	$314.81	5.86	0.38	0.85	0.32	0.05	0.05
2008	428	$309.20	5.99	0.14	-1.70	-0.38	-0.10	-0.12
2009	282	$225.02	6.41	0.01	1.45	0.31	-0.09	-0.12
2010	483	$225.39	6.68	0.01	0.87	0.34	0.10	0.09
2011	567	$207.16	6.30	0.00	-0.55	-0.13	0.03	0.02
2012	410	$207.62	6.62	0.00	0.46	0.24	-0.03	-0.04
Total	4600	$238.48	5.93	0.13	0.37	0.15	0.01	0.00

Assets are in millions, age is in years, returns are in percent per month and returns are net of fees.

Table 3: Monthly average characteristics of the performance measures

The table reports the mean, median, standard deviation, skewness, kurtosis, the minimum and maximum of the average monthly performance measures for the fund of fund X_1 and all hedge funds X_2 and the S&P 500, Russell 2000 and EMI emerging market index from January 31, 2001 until December 31, 2012. We also report the cut offs for the 20th, 40th, and 60th percentiles for all performance statistics. Jarque-Bera, $JB = n[(S22)/6) + \{(K—3)2\}/24]$, is a formal statistic for testing whether the returns are normally distributed, where n denotes the number of observations, *S* is skewness and *K* is kurtosis. This test statistic is asymptotically Chi-squared distributed with 2 degrees of freedom. The statistic rejects normality at the 1% level with a critical value of 9.2. All returns are in percent. MPPM(2) and MPPM(3) are manipulation proof performance measures of Goetzmann et al. (2007) with a risk aversion parameter of 2 and 3 respectively.

Statistic	*Rate of Return*					*Sharpe Ratio*				
	X_1	X_2	Russ	S&P	EMI	X_1	X_2	Russ	S&P	EMI
Mean	0.25	0.44	0.68	0.32	1.28	0.18	0.13	0.06	0.03	0.18
Median	0.57	0.66	1.63	1.00	1.28	0.26	0.29	0.22	0.20	0.19
St. Dev.	1.55	1.79	5.97	4.59	7.04	0.77	0.89	0.99	1.04	1.04
Skewness	-1.29	-0.84	-0.51	-0.59	-0.66	-0.47	-4.15	-0.67	-0.63	-0.49
Kurtosis	3.52	1.72	0.75	0.93	1.32	0.14	25.85	0.55	0.29	0.12
Min	-6.53	-6.47	-20.80	-16.80	-27.35	-2.16	-6.19	-3.58	-3.44	-2.95
20th Percentile	-0.79	-1.03	-4.28	-2.51	-3.32	-0.43	-0.27	-0.81	-0.80	-0.51
40th Percentile	0.15	0.19	0.05	0.06	-0.05	0.11	0.13	-0.03	-0.04	-0.02
60th Percentile	0.78	1.14	2.82	1.51	3.84	0.43	0.39	0.41	0.39	0.55
80th Percentile	1.48	1.78	5.32	3.72	7.14	0.86	0.66	0.89	0.89	1.01
Max	3.33	4.89	15.46	10.93	17.14	1.91	1.41	2.17	2.13	2.20
JB	41.56	27.00	36.61	34.15	27.44	54.49	3547.74	46.59	53.68	55.38
	MPPM(2)					*MPPM(3)*				
Mean	-0.01	0.01	-0.01	-0.02	-0.02	0.01	0.05	-0.01	-0.03	0.02
Median	0.02	0.03	0.02	0.00	0.05	0.04	0.14	0.03	0.05	0.12
St. Dev.	0.08	0.10	0.10	0.08	0.21	0.22	0.32	0.23	0.21	0.34
Skewness	-1.40	-1.36	-1.53	-1.22	-0.75	-0.42	-0.96	-0.50	-0.79	-1.01
Kurtosis	1.88	3.15	3.66	1.36	0.12	0.16	0.89	0.24	0.13	0.94
Min	-0.27	-0.43	-0.49	-0.29	-0.61	-0.61	-0.92	-0.66	-0.63	-0.99
20th Percentile	-0.05	-0.05	-0.06	-0.07	-0.21	-0.16	-0.19	-0.19	-0.23	-0.21
40th Percentile	-0.01	0.00	-0.01	-0.02	0.02	-0.03	0.07	-0.05	0.02	0.02
60th Percentile	0.03	0.05	0.04	0.03	0.08	0.08	0.18	0.06	0.06	0.16
80th Percentile	0.05	0.08	0.07	0.05	0.14	0.19	0.28	0.17	0.13	0.26
Max	0.12	0.18	0.17	0.11	0.42	0.48	0.62	0.47	0.41	0.60
JB	54.26	44.78	58.62	51.82	63.28	52.48	48.73	51.90	64.31	50.02

Table 4: Comparing hedge fund performance with the stock market

This table reports the first and second order stochastic dominance tests (s) to determine if the fund of fund (X_1) and overall universe of US dollar hedge funds (X_2) outperform the market according to the Sharpe ratio and the Manipulation Proof Performance MPPM using a risk aversion parameter of 2 and 3. Panels A, B and C compare hedge funds to the Russell 2000, S&P 500 and the MSCI emerging market indices respectively.

	s	$H_0^1: X_1 \succ_s Y_j$	$H_0^2: Y_j \succ_s X_1$	$H_0^1: X_2 \succ_s Y_j$	$H_0^2: Y_j \succ_s X_2$
Panel A:			*R2000*		
Sharpe	1	0.009	0.025	0.000	0.004
	2	0.973	0.009	0.570	0.009
MPPM(2)	1	0.000	0.008	0.000	0.001
	2	0.763	0.003	0.581	0.007
MPPM(3)	1	0.000	0.000	0.000	0.027
	2	0.774	0.008	0.568	0.005
Panel B			S&P500		
Sharpe	1	0.086	0.000	0.000	0.001
	2	0.981	0.001	0.817	0.005
MPPM(2)	1	0.000	0.063	0.000	0.000
	2	0.988	0.699	0.799	0.999
MPPM(3)	1	0.000	0.000	0.000	0.000
	2	0.502	0.463	0.999	0.991
Panel C			MSCI		
Sharpe	1	0.001	0.003	0.002	0.000
	2	0.675	0.006	0.614	0.002
MPPM(2)	1	0.000	0.000	0.000	0.000
	2	0.999	0.669	0.644	0.998
MPPM(3)	1	0.000	0.000	0.000	0.000
	2	0.582	0.483	0.562	0.477

Table 5: Comparing top and mediocre hedge fund performance

This table reports the first and second order stochastic dominance tests (s) to determine if the top quintile Z_5 fund of fund X_1 and overall universe of US dollar hedge funds X_2 outperform the mediocre quintile Z_3 for *t* months out of sample according to the Sharpe ratio and the Manipulation Proof Performance measure MPPM using a risk aversion parameter of 2 and 3.

		X_1		X_2	
t	s	$H_0^1: Z_5 \succ_s Z_3$	$H_0^1: Z_3 \succ_s Z_5$	$H_0^1: Z_5 \succ_s Z_3$	$H_0^1: Z_3 \succ_s Z_5$
Panel A		*Sharpe Ratio*			
1	1	0.995	0.082	0.888	0.000
	2	0.997	0.000	0.999	0.000
6	1	0.882	0.930	0.983	0.018
	2	0.992	0.468	0.999	0.000
12	1	0.283	0.999	0.898	0.030
	2	0.746	0.477	0.999	0.016
18	1	0.999	0.988	0.970	0.041
	2	0.921	0.214	0.970	0.032
24	1	0.905	0.999	0.998	0.005
	2	0.355	0.696	0.999	0.009
Panel B		*MPPM(2)*			
1	1	0.991	0.000	0.989	0.000
	2	0.999	0.000	0.999	0.000
6	1	0.999	0.041	0.993	0.000
	2	0.992	0.000	0.999	0.000
12	1	0.775	0.531	0.494	0.978
	2	0.999	0.331	0.956	0.720
18	1	0.420	0.999	0.188	0.999
	2	0.503	0.970	0.426	0.988
24	1	0.427	0.999	0.210	0.999
	2	0.560	0.514	0.595	0.892
Panel C		*MPPM(3)*			
1	1	0.987	0.000	0.945	0.000
	2	0.999	0.000	0.999	0.000
6	1	0.987	0.035	0.991	0.000
	2	0.999	0.000	0.999	0.000
12	1	0.223	0.999	0.716	0.723
	2	0.145	0.813	0.995	0.509
18	1	0.423	0.999	0.157	0.999
	2	0.634	0.847	0.408	0.989
24	1	0.995	0.999	0.384	0.999
	2	0.404	0.780	0.614	0.534

Table 6: Top and mediocre hedge fund risk profiles

This table reports the quantile response, at the 25th, 50th and 75th quantiles, of the returns for top performing Z_5 and mediocre performing funds Z_3 (according to the manipulation proof performance measure with a risk parameter of 3) of the fund of fund portfolios six months out of sample in response to a unit change in the risk factors for market risk (MKTRF), size (SMB), value (HML), momentum (MOM), long term momentum reversal (LTR) and liquidity (AGGLIQ).

Quantile		F_5		F_3	
		Coefficient	Bootstrap S.E.	Coefficient	Bootstrap S.E.
Q25	*CONS*	-0.755**	0.287	-0.365**	0.189
	MKTRF	0.362***	0.085	0.277***	0.049
	SMB	0.150	0.159	0.054	0.054
	HML	0.067	0.190	0.114	0.089
	MOM	0.214***	0.072	0.075***	0.030
	LTR	-0.148	0.153	-0.205***	0.079
	AGGLIQ	0.842	4.420	4.067*	2.140
	Pseudo R^2	0.225		0.413	
Q50	*CONS*	0.647*	0.324	0.310***	0.114
	MKTRF	0.295***	0.083	0.236***	0.045
	SMB	0.037	0.100	0.058	0.053
	HML	-0.070	0.156	0.056	0.045
	MOM	0.130**	0.079	0.073***	0.022
	LTR	0.014	0.150	-0.118**	0.058
	AGGLIQ	-4.523	4.321	4.173*	2.095
2	Pseudo R	0.131		0.320	
Q75	*CONS*	1.985***	0.325	0.779***	0.110
	MKTRF	0.281**	0.107	0.206***	0.037
	SMB	-0.009	0.119	0.049	0.049
	HML	-0.031	0.131	0.059	0.063
	MOM	0.150**	0.071	0.069**	0.032
	LTR	0.011	0.140	-0.033	0.052
	AGGLIQ	-0.799	4.849	1.248	2.553
	Pseudo R^2	0.153		0.255	

***,**,* statistically significant at the 1, 5 and 10% level respectively. SE are the bootstrapped standard error obtained with 1000 replications.

Figure 1: This figure graphs the estimates of equation (4) with the quantile of F_5 as dependent variable. Performance is according to proof performance measure with a risk parameter of 3 with excess returns as the dependent variable.

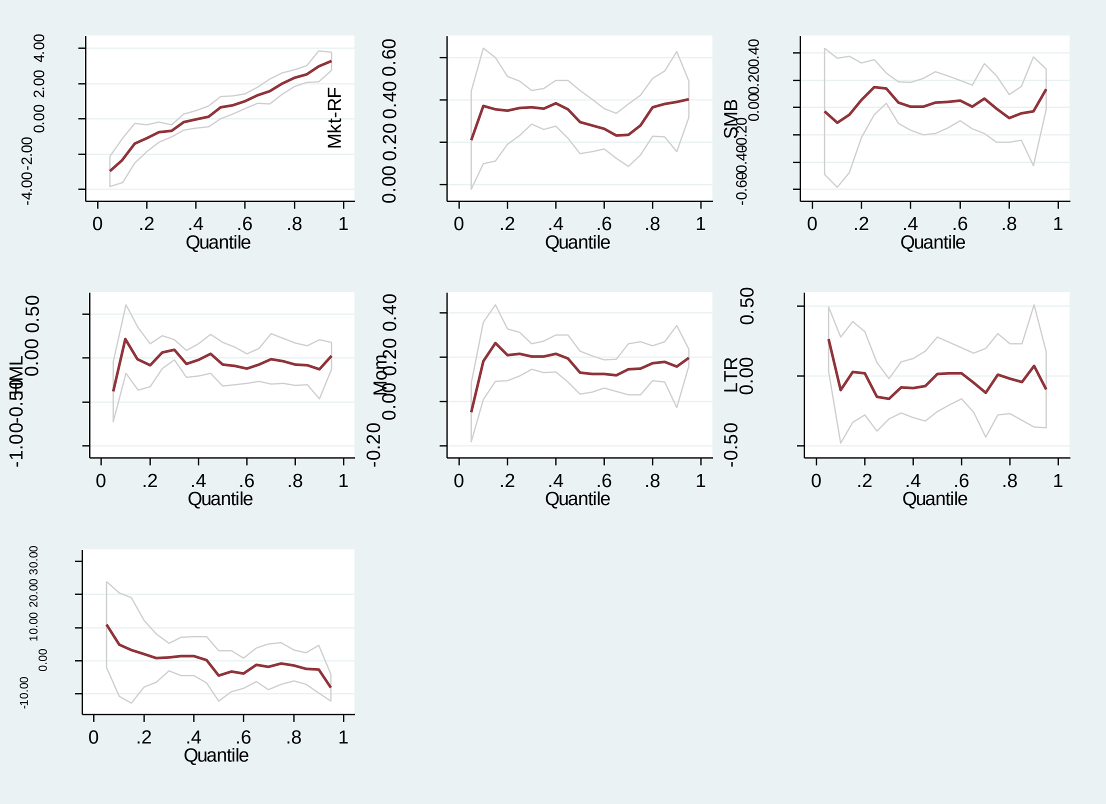

Figure 2: This figure graphs the estimates of equation (4) with the quantile of F_3 as dependent variable. Performance is according to proof performance measure with a risk parameter of 3 with excess returns as the dependent variable.

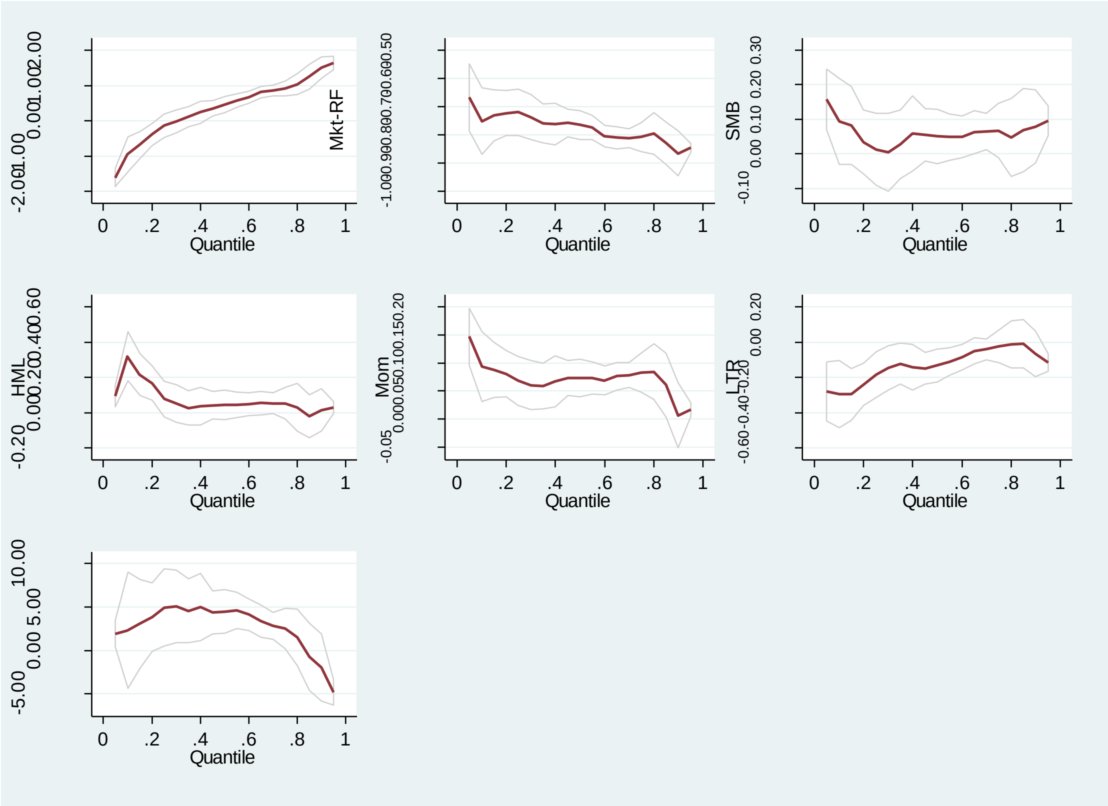

Figure 3 Time variation of the risk factors for top performing funds

These figures show the time varying estimated coefficients of the risk factors in equation (4) and their upper UB and lower bounds LB that explains the six month out of sample net excess rate of return for the top quintile performing fund of fund hedge funds according to the manipulation proof performance measure with a risk aversion parameter of 3. The risk factors are the market excess rate of return MRTRF and the size SMB, growth HML, momentum MOM, momentum reversal LTR and liquidity AGGLIQ factors.

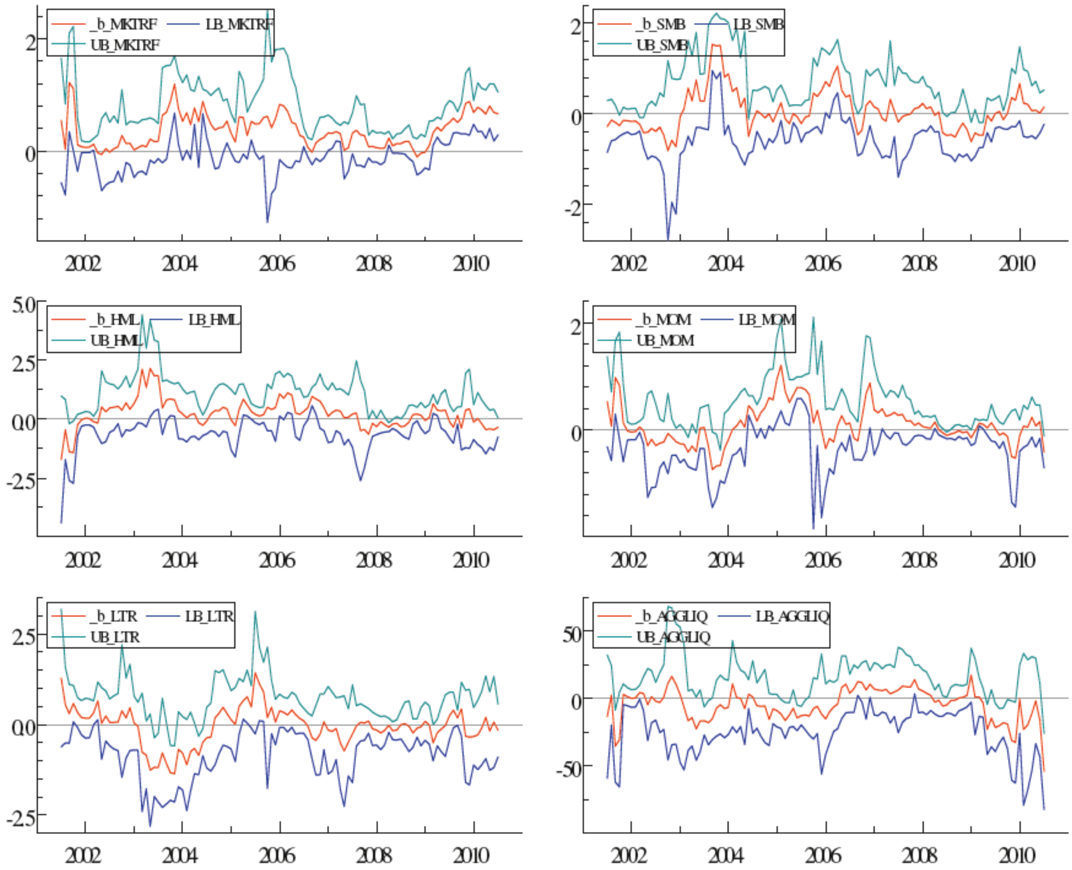

Figure 4: Time variation of the risk factors for mediocre performing funds

These figures show the time varying estimated coefficients of the risk factors in equation (4) and their upper UB and lower bounds LB that explains the six month out of sample net excess rate of return for the third (mediocre) quintile performing fund of fund hedge funds according to the manipulation proof performance measure with a risk aversion parameter of 3. The risk factors are the market excess rate of return MRTRF and the size SMB, growth HML, momentum MOM, momentum reversal LTR and liquidity AGGLIQ factors.