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Abstract

We investigate why top performing hedge funds are successful. We find evidence that top performing hedge funds follow a different strategy than mediocre performing hedge funds as they accept risk factors that do and avoid factors than do not anticipate the troubling economic conditions prevailing after 2006. Holding alpha performance constant, top performing funds avoid relying on passive investment in illiquid investments but earn risk premiums by accepting market risk. Additionally, they seem able to exploit fleeting opportunities leading to momentum profits while closing losing strategies thereby avoiding momentum reversal.

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

***JEL* classification:** G11; G12; G2

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1. Introduction

The hedge fund industry continues to attract enormous sums of money. For example, BarclayHedge reports that the global hedge fund industry has more than $3.2 trillion of assets under management as of March 2018.[1]Yet, due to the light regulatory nature of the industry, we know very little about how these assets are managed or what strategies hedge fund managers pursue.

We examine the structure of significant risk factors that explain the out of sample net excess returns of successful hedge funds to develop some information concerning the strategies followed by successful hedge funds. This is a departure from prior work that examines the characteristics (Boyson (2008), the sex of managers (Aggarwal and Boyson 2016) or the fee structures (Agarwal *et al.* 2009) of successful hedge funds. In other words, rather than examine the visible characteristics, we examine the risk factors accepted by hedge funds to uncover information concerning the behaviour of hedge funds.

To investigate top hedge funds, we need to identify top performing funds and to determine how long their superior performance persists. Therefore, we need to address two prerequisite questions, namely, do hedge funds perform as well as or better than market benchmarks and, for the top performing funds, does top performance persist? We need to know whether hedge funds, as a class, outperform, perform as well, or underperform the market to appreciate what top performance means. We also need to know how long the superior performance of top hedge funds persists to identify the data we need to interrogate the successful strategies followed by these hedge funds.

[1] http://www.barclayhedge.com/research/indices/ghs/mum/HF_Money_Under_Management.html

The issues highlighted above have important implications; it is therefore not surprising that a lot of attention has been paid to technical issues. There is now substantial evidence that the underlying generating processes of the distributions of hedge fund returns are fat tailed and nonlinear. When fund returns are not normally distributed mean and standard deviation are not enough to describe the return distribution. Researchers therefore sought to replace traditional risk measures with risk measures that incorporate higher moments of the return distributions to analyse tail risk (see for example Liang and Park, 2007; 2010). To address the issue of nonlinearity some researchers have turned to non-parametric techniques. For example, Billio *et al.* (2009b) use smoothing methods to estimate the conditional density function of hedge fund strategies. Non-parametric methods allow for non-normal distribution of returns and non-linear dependence with risk factors. Recently, the non-parametric literature has used the estimated density function in the context of stochastic dominance analysis. It is in this strand of the literature that this paper is related to.

The present study relates to work by Bali *et al*. (2013) who use an almost stochastic dominance approach and the manipulation proof performance measure MPPM to examine the relative performance of hedge fund portfolios. Unlike the prior literature, we use non-parametric techniques that allow us to conduct formal statistical tests under general assumptions of the distribution of hedge fund returns. Specifically, we employ stochastic dominance tests to determine if the hedge fund industry outperformed or underperformed the market in recent years and whether and for how long top performing funds persistently outperform mediocre performing hedge funds using the methods proposed by Linton, Maasoumi and Whang (2005). Linton *et al.* (2005) propose consistent tests for stochastic dominance under a general sampling scheme that includes serial and cross dependence among hedge funds distributions. The test statistic

requires the use of empirical distribution functions of the compared hedge fund strategies. Linton *et al.* (2005) suggest using resampling methods to approximate the asymptotic distribution of the test to produce consistent estimates of the critical values of the test.

In the literature, a few related papers use the stochastic dominance principle in the context of hedge fund portfolio management. For example, Wong *et al*. (2008) employ the stochastic dominance approach to rank the performance of Asian hedge funds. Similarly, Sedzro (2009) compare the Sharpe ratio, modified Sharpe ratio and DEA performance measures using stochastic dominance methodology. Abhyankar *et al*. (2008) compare value versus growth strategies. In a related study, Fong *et al*. (2005) use stochastic dominance test in the context of asset-pricing.

However, most of these empirical works use stochastic dominance tests that work well under the i.i.d. assumption but are not suitable for many financial assets. For example, the popular stochastic dominance test suggested by Davidson and Duclos (2000) used in most of these studies is designed to compare income distribution functions and the inference procedure is invalid when the assumption of i.i.d. does not hold. Several studies (see Brooks and Kat, 2002) have shown that the distributions of hedge fund returns are substantially different from i.i.d. since they exhibit high volatility and highly significant positive first order autocorrelation. Bali *et al*. (2013) also find cross dependence with stock markets. All these features which are intrinsic in the data at hand invalidate the use of a stochastic dominance tests that are not robust to departure from the i.i.d. assumption.

Another possible drawback of the related literature is that these empirical works compares the probability distribution functions of hedge fund portfolios only at a fixed number of arbitrarily chosen points. This can lead to lower power of the inference

procedure in cases where the violation of the null hypothesis occurs on some subinterval lying between the evaluation points used in the test. In general, stochastic dominance tests may prove unreliable if the dominance conditions are not satisfied for the points that are not considered in the analysis.

Unlike related studies, the inference procedure adopted in this paper allows us to overcome the above issues by examining cumulates of the entire empirical distribution. The adopted stochastic dominance inference procedure is robust to departures of cross-dependency between random variables and serial correlation. It is also robust to unconditional heteroschedasticity. This constitutes a significant departure from the traditional stochastic dominance inference procedures which rely on the problematic i.i.d. assumption of hedge fund return distributions.

Once identifying that hedge funds perform as well as the market and finding that top performance persists for six months, we proceed to the main empirical issue by employing quantile regressions to examine the risk factors accepted by top and mediocre performing funds. Our research is in the spirit of Billio *et al.* (2009b) who also use non-parametric regression to analyse the relationship between hedge funds indices and stock market indices.

Standard regression specifications for hedge funds used in the related literature model the conditional expectation of returns. However, these regression models describe only the average relationship of hedge fund returns with the set of risk factors. This approach might not be adequate due to the characteristics of hedge fund returns. The literature (see, for example, Brooks and Kat, 2002) has acknowledg**e** that, due to their highly dynamic nature, hedge fund returns exhibit a high degree of non-normality, fat tails, excess kurtosis and skewness. In the presence of these **c**haracteristics the

conditional mean approach may not capture the effect of risk factors on the entire distribution of returns and may provide estimates which are not robust.

Unlike standard regression analysis, quantile regressions examine the quantile response of the hedge fund return at say the 25^{th} 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 out of sample return of hedge funds respond 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 each of the systematic risk factors.

Accordingly, our empirical investigation proceeds in four stages. First, we examine whether hedge funds have outperformed several market benchmarks. We find that despite the relatively low hedge fund returns in recent years, the market does not second order stochastically dominate hedge funds from January 2001 to December 2012.

Second, we examine whether top performing hedge funds persistently outperform mediocre performing hedge funds out of sample even if we include the challenging economic conditions of recent years. We find that the top performing quintile of hedge funds does 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 (Gonzalez *et al.* 2015, Boyson 2008) or three years (Ammann *et al.* 2013) reported earlier by authors who use less robust parametric techniques. In contrast, the Sharpe ratio sometimes finds evidence of longer term persistence. Billio et al. (2013) find that the MPPM measures can be dominated by the mean, especially when using relatively low risk aversion parameters and this could explain why conclusions reached by MPPM measures deviate from the Sharpe ratio. In

any event we conclude that top performing funds persistently outperform mediocre funds for at least six months.

Third, we examine the role liquidity as well as other risk factors, such as momentum, play in achieving net excess rates of return out of sample. We also examine the structure of asset-based risk factors via Fung and Hsieh (2004). We do this for funds of superior and mediocre performance to determine whether top performing funds take on a distinctively different risk profile, implying they follow a distinctive strategy, than mediocre performing funds. An important caveat is that we are examining these factors as slope coefficients estimated via quantile regression methods, so we must assume alpha performance is constant. We find that top performing fund returns are driven by a different risk profile than is evident for more modestly performing funds.

Fourth, we investigate the behavior of risk factors accepted by top and mediocre performing hedge funds by examining the time series values of their coefficients 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 in the months leading up to the financial crisis period but by 2008, the confidence envelope for 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, the dispersion of coefficient values for the long-term reversal and liquidity factors is delayed until the actual recession of 2008. This suggests that the long-term reversal and aggregate liquidity factors, factors that significantly explain mediocre hedge fund performance, merely react to the 2008 recession. In contrast, the

market and the momentum factors, factors that are significant in explaining top fund performance, anticipate the liquidity crisis and subsequent recession.

Stivers and Sun (2010) also find that the momentum factor is procyclical, but they do not examine the role of other factors, such as liquidity and momentum reversal. Moreover, while these results also support Kacperczyk *et al.* (2014) who find evidence that market timing is a task that top performing mutual fund managers can execute, we find evidence that top performing hedge funds have but mediocre performing hedge funds do not have this capability. Additionally, we uncover evidence of what systematic risk factors top funds exploit and what systematic risk factors they avoid.

A possible drawback of our stochastic dominance analysis is that preserving the characteristics of the data may not control for the issue of returns smoothing. Many scholars have observed that one consequence of smoothing is to make hedge funds returns appear less risky. To address this important issue, the stochastic dominance analysis is repeated using unsmoothed hedge fund return data.[2] We find that our results are replicated using unsmoothed data. Specifically, hedge funds perform at least as well as the market, top performance persist for at least six months and mediocre performing funds accept additional risk factors for liquidity and momentum reversal.

In section 2 we report some related literature while Section 3 describes the data. Our empirical analysis proceeds in Section 4 and 5 while Section 6 adjusts for return smoothing. In section 7 we generate additional insights by examining the structure of asset based systematic risk factors via the Fung and Hsieh (2004) seven factor model. Section 8 summarizes and concludes.

[2] We need to repeat our analysis on unsmoothed data using somewhat different procedures because Linton et al. (2005) adjusts for correlation no matter what the cause including smoothing.

2. Literature review

The case for hedge funds "beating" the market is not clear. Weighing up all the evidence, Stulz (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 and CTA funds 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 *et al.* (2013) 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. This has an impact on this paper because we are interested in developing insights of the strategies followed by successful fund managers and not of the strategies followed by the best fund managers in an underperforming asset class.

Some research strongly supports persistence, other research is more equivocal. Formed on Fung and Hsieh (2004) alphas, Ammann *et al.* (2013) find three years while Boyson (2008) and Gonzalez *et al.* (2015) find two years of performance persistence for top funds. Agarwal and Naik (2000) note that a two-period model for performance persistence can be inadequate when hedge funds have significant lock-up periods. Using a more exacting multi-period setting, they find performance persistence is short term in nature. Jagannathan Malakhov and Novikov (2010) find performance persistence only for top performing and not for poorly performing funds suggesting that performance persistence is related to superior management talent. Ammann *et al.*

(2013) find that strategy distinctiveness as suggested by Sun *et al.* (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 *et al.* (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. Eling (2009) finds that performance persistence appears to be related to the methodology used to detect it.

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. Meanwhile, 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. Gonzalez *et al.* (2015) find that when evaluated by the Sharpe and information ratios, performance persistence is more doubtful according to the doubt ratio of Brown *et al.* (2010), whereas performance persistence is less doubtful for portfolios formed on alpha and the MPPM. Finally, O'Doherty *et al.* (2016) develop a pooled benchmark and demonstrate that Fung and Hsieh (2004) alphas and other

performance measures derived from common parametric benchmark models understate performance and performance persistence.

Another strand of the hedge fund literature 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 Schuhmacher (2007) find that the ranking of hedge funds by the Sharpe ratio is virtually identical to twelve alternative performance measures. Goetzmann *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. Billio et al. (2013) discover that the MPPM measure, especially when using lower risk aversion parameters, is strongly influenced by the mean of returns and does not fully consider other moments of the distribution of returns such as skewness and kurtosis. To adjust for this deficiency, Billio et al. (2013) develop the N performance measure which more fully considers the first four moments of the return distribution.

A final strand of the literature examines the structure of risk factors that explains hedge fund returns. Titman and Tiu (2012) find an inverse relation between the R-square of linear factor models and hedge fund performance suggesting that better performing funds hedge systematic risk. Sadka (2010, 2012) demonstrate that liquidity risk is positively related to future returns suggesting that performance is related to

systematic liquidity risk rather than management skill. After controlling for share restrictions (lock up provisions and the like), Aragon (2007) finds that alpha performance disappears. Moreover, there is a positive association between share restrictions and underlying asset illiquidity suggesting that share restrictions allow hedge funds to capture illiquidity premiums to pass on to investors.

Meanwhile, Billio *et al.* (2009a) find that when volatility is high, hedge funds have significant exposure to liquidity risk and Boyson *et al.* (2010) find evidence of hedge fund contagion that they attribute to liquidity shocks. Chen and Liang (2007) find evidence that market timing hedge funds have the ability to time the market for anticipated changes in volatility, returns and their combination while Cao *et al*. (2013) find that mutual fund managers have the ability to time the market for anticipated changes in liquidity. More recently, Bali *et al.* (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.

3. Data

The data we use come 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 factors from the French Data library, the Fung and Hsieh factors from the David Hsieh data library and the aggregate liquidity factor from the Lubos Pastor Data library. Finally, equity index information is from DataStream. Most of the literature (see Stulz 2007) benchmark hedge fund performance relative to the large cap S&P 500. For robustness, we include the small cap dominated Russell 2000 and the

emerging market MCSI indices to represent alternatives hedge fund investors could accept as benchmarks.

We select all US dollar hedge funds that have three years of historical performance from the date first listed in TASS prior to our start date of January 31, 2001. We need to have three years of data to avoid multi-period sampling bias and to avoid back fill bias so the first three years of data are not used to measure performance.[3] 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 *et al.* 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. 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 month observations, including dead 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.

We collect all monthly holding period returns net of fees. We adjust for survivorship bias by including all funds both live and dead. We calculate the Sharpe ratio as the net 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 net excess returns.

[3] Using data from the date added to the TASS data base may not eliminate back fill bias in TASS. TASS had a major update in 2011 by listing data from other databases. Some of this data could be back filled data so deleting data prior to the date of listing on TASS is no guarantee that back fill bias has been eliminated. It is recommended that at least the first 18 to 24 months of data be deleted to more reliably mitigate against back fill bias.

[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.

Another empirical issue is data smoothing where hedge fund managers do not always report gains or losses promptly leading to serial dependence in the return data. If left unadjusted, the test statistic could be inflated. We use Linton, Maasoumi and Whang (2005) that obtains consistent estimates of the critical values even when the data suffers from such serial dependence. For robustness we later repeat our empirical work on unsmoothed data using simpler econometric procedures to find the same results we report below using Linton, Maasoumi and Whang (2005) on the TASS reported data.

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

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

where $t = 1, \ldots, T$ and A is the risk aversion parameter, r_t is the net 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 the 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 and follow Goetzmann *et al.* (2007) and Brown *et al*. (2010) by using a risk aversion parameter A of 3. Billio *at al.* (2013) find that the MPPM measure is strongly influenced by the mean of returns and does not fully consider other moments of the distribution of returns such as skewness and kurtosis. This effect is most strongly felt

for MPPM when the risk aversion coefficient is low. Therefore, for robustness, we compute the MPPM over a wide variety of risk aversion parameters of 2, 3, 6 and 8.[5]

Table 1 reports that our data consists of 4,600 funds with 176,483 fund month observations. This sample is smaller than Bali *et al.* (2013) who include non US dollar denominated funds but is comparable in size to Ammann *et al.* (2013) and Hentati-Kaffel and Peretti (2015). A striking fact is the huge attrition rate of hedge funds, less than one half of all 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 is consistent with the continuing decline in hedge fund net returns reported by Dichev and Yu (2011). As the MPPM measures the certainty equivalent of realized returns for a representative investor of a given degree of risk aversion, the investor's assessment of performance declines as the risk aversion parameter increases.

<<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 for investors with a risk aversion

[5] We neglect to report the results for MPPM(6) as they are very similar to the results when using MPPM(8). These results are available from the corresponding author upon request.

parameter of 2 (8), hedge funds were unable to return a certainty equivalent premium above the risk-free rate for five (eight) 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 seek information concerning the generic strategies followed by "top" funds and are less interested in strategies confined to a given hedge fund class. Strategies of aggregations by style cannot be easily generalized because the results will be tainted by the peculiarities of a given hedge fund class (style) and will be difficult to assess as benchmarks need to be style consistent (see Mason and Skinner, 2016). Therefore, we need to aggregate the hedge fund data in some way. We chose to aggregate our data by fund of funds, the largest grouping of hedge funds with 1,273 funds and 45,700 fund month observations and by all hedge funds. Fung *et al.* (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 a wide range of risk aversion parameters from 2 to 8 for the fund of fund, all hedge funds and for the S&P 500, Russell 2000 and MSCI emerging market indices are reported in Table 3. 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.

4. Stochastic dominance tests for hedge funds performance

In this section, we develop two procedures for comparing distributions of hedge funds returns. First, we are interested in testing whether hedge funds outperform or underperform the market and second, whether top performing funds outperform mediocre funds out of sample and for how long. Our procedures for testing differences between distribution functions rely on the concept of first and second order stochastic dominance. Stochastic dominance analysis provides a utility-based framework for evaluating investors' prospects under uncertainty, thereby 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 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 and therefore no rational investor would choose the dominated asset.

Testing for stochastic dominance is 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 tests rely 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 several 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 *et al.* (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.

4.1 Testing for hedge fund performance

Classifications of "top performance" within an asset class (i.e. hedge funds) is relative so we need some check to make sure that "top performing" hedge funds have in fact superior performance in an absolute sense. One way of doing this is to compare the performance of hedge funds against alternative classes of assets. We chose as our benchmarks "the market" as represented by the large cap S&P 500, the smaller cap Russell 2000 and an internationally diversified portfolio as represented by the MCSI index. The idea is that if hedge funds, as an asset class, perform as well or better than these assets, then we have assurance the very best performing hedge funds have indeed superior performance.

Accordingly, our first stochastic dominance test is to determine if the returns of portfolios of all fund of fund and all hedge funds outperform or underperform the market using four performance criteria, namely the Sharpe ratio, MPPM(2), MPPM(3) and MPPM(8). For each hedge portfolio, we test to determine if the returns first or second order stochastically dominate, or the reverse, three market indexes, specifically, the S&P 500, Russell 2000 and the MSCI emerging market indexes.

The essence of our test strategy is as follows. Let X_i be the performance of the hedge fund portfolio i (for $i = 1,2; fund\ of\ funds, all\ hedge\ funds$) and let Y_j denote the

performance of the stock market index j (for $j = 1, \dots, 3;\ S\&P\ 500, Russel\ 2000, MSCI$). 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 being the negation of the null hypothesis for both H_0^1 and $H_{0.}^2$ We infer that returns of the hedge fund 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 hedge fund portfolio returns if we accept H_0^2 and reject H_0^1. 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.

Panels A, B and C in Table 4 report the results of this stochastic dominance test for the S&P 500, Russel 2000 and MSCI indexes respectively. For each panel, empirical p-values test whether the fund of fund aggregation of hedge funds first and second order dominate the candidate benchmark (column three) or the reverse (column four). 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 the Appendix with 1,000 bootstrap replications. Similarly, columns five and six report the p-values that tests whether the aggregation of all hedge funds X_2 first or second order dominate the candidate stock market index or the reverse.

<<Table 4 about here>>

In Table 4, rejection of the null hypothesis is based on small *p*-values of the test statistic described in the Appendix. Table 4 reports that hedge funds do not first order stochastic dominate all stock market benchmarks 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 hedge fund portfolio X_i regardless of risk.

Panels A and C in Table 4 shows that for the MPPM performance measures, neither the null hypothesis $H_0^1: X_i \succ_{s:=2} Y_j$ nor $H_0^2: Y_j \succ_{s:=2} X_i$ can be rejected for the S&P 500 and MSCI stock market benchmarks. Therefore, the stochastic dominance test is inconclusive for the MPPM(2), MPPM(3) and MPPM(8) performance measures. In contrast, the hedge fund industry second order dominates the stock market according to the Sharpe ratio. However, the test results are different in Panel B. Here we see that the hypothesis $H_0^1: X_i \succ_{s:=2} Y_j$ cannot be rejected no matter which performance measure we consider, so we conclude that the hedge fund industry second order dominates the stock market as represented by the Russell 2000.

To reconcile the results by performance measure, we note that the Sharpe ratio is by construction sensitive to departures from normality. As we document in Table 3, our monthly hedge fund returns are non-normal, so this could explain most of the differences in results according to the Sharpe ratio and the MPPM measures. Moreover, according to Billio *et al.* (2013), the MPPM measures can be dominated by the mean, especially when using relatively low risk aversion parameters and this too could explain why the results obtained by the Sharpe ratio can deviate from results obtained by the MPPM measures. The later effect can be seen in Panel B where the MPPM(8) measure

is much more in line with the Sharpe performance measure in suggesting that the fund of fund aggregation of the hedge fund industry second order dominates the Russel 2000 benchmark. Specifically, in contrast to MPPM(2) and MPPM(3), the Sharpe and MPPM(8) performance measures accept $H_0^1: X_{i=1} \succ_{s:=2} Y_{j=2}$ at very low empirical significance levels (above 0.95) and reject $H_0^2: Y_{j=2} \succ_{s=2} X_{i=1}$ at very high empirical significance levels (below 0.01).

In any event, we conclude that despite the declining returns suffered by the hedge fund industry in recent years, the hedge fund industry at least did not underperform the market. This conclusion is consistent with Bali *et al.* (2013), who while not formally testing for stochastic dominance, find that the fund of fund hedge fund strategy does not outperform the S&P500 according to the MPPM.

4.2 Performance Persistence of Top Performing Hedge Funds

We now consider our second stochastic dominance test, namely whether top performing hedge 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), MPPM(3) and MPPM(8) performance measures and compare the performance of these portfolios to the performance of similarly formed mediocre (third) quintile portfolios. These quintile portfolios, once formed, are held for twenty-four months. We avoid comparing top to bottom quintile portfolios because hedge funds in the bottom performing quintile are subject to a second round of survivorship bias as poorly

performing funds continue to leave the TASS database during the twenty-four months out of sample period.[6]

Specifically, we form 120 monthly portfolios from January 31, 2001 to December 31, 2010. 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. We then hold these portfolios for twenty-four months and then measure the performance of these portfolios by quintile and by performance measure at six, twelve, eighteen and twenty-four months out of sample. 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 fund portfolio X_i, 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 $k \in \{3,5\}$ which we refer to as mediocre and top quantile, respectively, and we test the following hypotheses

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

[6] Out of sample data can create a second round of survivorship bias because funds continue to withdraw from the data during the out of sample period, see Gonzalez *et al.* (2015) for a detailed explanation.

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 quintile hedge fund portfolio Z_5 stochastically dominates the returns from the mediocre hedge fund portfolio Z_3 if we accept H_0^1 and reject H_0^2. Conversely, we infer that the returns of the mediocre portfolio Z_3 stochastically dominate the top fifth quintile portfolio returns Z_5 if we accept H_0^2 and reject H_0^1. In cases where neither of the null hypotheses can be rejected, we infer that the stochastic dominance test is inconclusive.

Table 5 reports the results of our performance persistence tests. Table 5 is organized into four panels, each panel reporting whether the portfolio formed from top funds stochastically dominate the portfolio formed from mediocre funds six, twelve, eighteen and twenty-four months out of sample according to the Sharpe ratio, the MMPM(2), MPPM(3) and MPPM(8) 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>>

In contrast to Eling's (2009) conclusion, we obtain different views of performance persistence according to which performance statistic is considered.[7] Looking first at the

[7] We should note that Eling (2009) did not evaluate the recently developed MPPM and so had no opportunity to examine whether the length of persistence varied according to this measure in comparison to other performance measures.

Sharpe ratio, for the fund of funds portfolio X_1,we are unable to find any evidence that top funds Z_5 first or second order dominate the mediocre performing hedge funds Z_3. In contrast, looking at the aggregation of all hedge funds X_2, the portfolio of top hedge funds Z_5 first and second order stochastically dominate mediocre hedge funds Z_3 up to twenty-four months out of sample.

In contrast to the Sharpe ratio, we find that the corresponding dominance tests when using the more robust MPPM(2), MPPM(3) and MPPM(8) performance measures are consistent for the portfolio of all hedge funds and for the fund of fund hedge funds. Specifically, top quintile funds first and second order dominate mediocre funds up to six months out of sample. Therefore, unlike Slavutskaya (2013), we do find some evidence of performance persistence for top funds, but, at least according to the MPPM, persistence is much more modest than found by Gonzalez *et al.* (2015), Ammann *et al.* (2013) and Boyson (2008). In any event we conclude that top performing funds persistently outperform mediocre funds for at least six months.

5. **Risk profile of hedge funds**

Table 5 shows that top quintile performing hedge funds continue to outperform the corresponding mediocre hedge funds for at least six months out of sample. This suggests that top performing funds are different in some way that enables them to achieve distinctly superior performance. To discover how these top performing funds

are different from mediocre funds, we examine the risk profiles of top and mediocre funds six months after they were formed.

We use the Fama and French (1995) empirical asset pricing model as the basic multi-factor model that describes the risks that hedge fund managers take to generate returns.[8] 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 market priced risk factors.

We explain out of sample net excess returns of top and mediocre performing hedge funds by quintile for the fund of fund sector.[9] The procedure is to regress excess hedge fund returns by quintile at six months out of sample on risk factors for the excess market return ($MKTRF_t$), for the Fama and French (1995) risk factors for size (SMB_t) and value (HML_t), the Carhart (1997) risk factor for momentum (MOM_t), for momentum reversal (LTR_t) and for the Pastor and Stambaugh (2003) liquidity factor ($AGGLIQ_t$).

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

$$F_{t,k} = Z_{t,k} - RF_t,$$

where $Z_{t,k}$ are the monthly rate of returns of the portfolio X_1 for six months after the portfolio was formed and RF_t is the one-month risk free rate of return from the French Data Library. Then, the model specified is as follows:

$$F_{t,k} = f(MKTRF_t, SMB_t, HML_t, MOM_t, LRT_t, AGGLIQ_t). \quad (2)$$

[8] We also examine the five factor Fama French (2015) model finding that the profitability RMW and investment CMA factors are not significant. For the sake of brevity, we do not report these results here but are available from the corresponding author upon request.

[9] For the sake of robustness, we also estimate the model using the data for all hedge funds and obtain similar results. The results are available from the corresponding author upon request.

We estimate Equation (2) 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. While the traditional linear regression model can address whether a given risk factor in Equation (2) affects the hedge fund conditional returns, it can't answer another important question: Does a one unit increase of a given risk factor of Equation (2) affect returns the same way for all points in the return distribution? Therefore, the conditional mean function well represents 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 (2) can be specified as

$$Q(\tau \mid R_t\text{=r}) = R'_t\beta(\tau), \qquad \text{for } 0 \leq \tau \leq 1 \qquad (3)$$

where $Q(\cdot) = \inf\{f_k : G(F_{t,k}) \geq \tau\}$ and $G(F_{t,k})$ is the cumulate density function of $F_{t,k}$. The vector R_t is the set of risk factors in Equation (2) and β is a vector of coefficients to be estimated. In Equation (3) the τ-quantile is expressed as the solution of the optimization problem

$$\hat{\beta}\,(\tau) = argmin \sum_{i=1}^{n} \rho_\tau(F_{t,k} - R_t'\beta) \qquad (4)$$

where $\rho_\tau(\xi) = \xi\big(\tau - I(\xi < 0)\big)$ and $I(\cdot)$ is an indicator function. Equation (4) is then solved by linear programming methods and the partial derivative:

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

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_t. As τ increases continuously from 0 to 1, it is possible to trace the entire distribution of $F_{t,k}$ conditional on R_t.

It is worth noting that the proposed estimation method is robust to heteroskedastic innovation in Equation (3). It is well known that return data have 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.

Table 6 reports the quantile regression estimates of Equation (3) for the top $F_{t,5}$ and mediocre $F_{t,3}$ performing portfolio excess returns six months out of sample. This table has three panels reporting the estimates of Equation (3) at the 25th, 50th and 75th quantiles. In column three, the estimated coefficients for Equation (3) for the top quintile of performing funds $F_{t,5}$ are reported, whereas column five reports the estimates for the mediocre performing funds $F_{t,3}$. In columns four and six, the corresponding bootstrapped robust standard errors for the estimated coefficients are reported. The standard errors were calculated by resampling the estimated residuals of Equation (3) using the non-parametric bootstrap method with 1000 replications.

<<Table 6 about here>>

Table 6 reports that top performing hedge funds have a distinctly different risk profile than mediocre funds. Only two factors are statistically significant for top performing funds, whereas mediocre performing funds often have up to four significant risk factors. Specifically, top performing funds have a statistically significant market risk and momentum factor at all three quantiles clearly stating that these factors are significant throughout a broad range of the distribution of top performing hedge fund returns and not just at the mean. 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 because 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 quantile is the same as top performing funds. This suggests that the very best of the mediocre performing hedge funds emulate top performing hedge funds.

Figures 1 and 2 provide a graphical view of the marginal effects of the risk factors on excess returns. Figure 1 and 2 correspond to the estimates in Table 6, but the estimates are reported for every risk quantile τ, with $0 \leq \tau \leq 1$. The bold line in Figure 1 shows the 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. Each graph in the figures depict the relation between the size of the coefficient and the risk quantile of a given risk factor for a given performance quintile as measured by the manipulation proof performance measure with a risk aversion parameter of 3.

In Figure 1, the second graph shows that for top performing funds $F_{t,5}$, as the market risk quantile of $MKTRF_t$ increases, the beta response coefficient increases at the extremes. This implies that performance for top funds is more sensitive to a one unit increase in market risk at the tails of the distribution of market risk. Moreover, the coefficient for market risk is always positive and statistically significant because zero is outside the confidence interval. Similarly, Figure 1 shows that the MOM effect for top funds is significantly positive for all but the very lowest quantiles.

<<Figures 1 and 2 about here>>

Looking at Figure 2, we see that for mediocre performing funds F_3, long term reversal LTR_t is significantly negative for all risk quantiles τ up to approximately 0.60. We also note that while Table 6 reports that liquidity is significant at the 10% level for the 25th and 50th quantiles, Figure 2 shows that this modest level of significance is due to a wide dispersion of this risk factor as the confidence envelop is wide. Moreover, this factor is significant, albeit at a modest level, over a broad range of quantiles from approximately the 20th to the 70th quantiles.

Finally, we estimate the time varying coefficients for Equation (3). 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. To avoid clutter, we focus on the conditional median equation (i.e. the 50th quantile) in (3).

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 Equation (4) for each month using a 12-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 widen in 2006 and early 2007 suggesting that these risk factors were subject to greater uncertainty in the run up to the recent financial crisis. Meanwhile, the liquidity and momentum reversal factors 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. While some of these results are in line with Kacperczyk et al. (2014) who find that market timing is a task that only skilled managers can perform, we also discover, evidently, which systematic risk factors top funds accept and which systematic factors they avoid in achieving top performance.

<<Figures 3 and 4 about here>>

6. Return smoothing and its implication for performance analysis of hedge funds

The analysis in Section 4 was conducted assuming that due to their highly dynamic complex nature, hedge fund returns exhibit a high degree of non-normality, fat tails,

excess kurtosis and skewness which invalidate the traditional mean-variance framework of Markowitz (1959). Our assumption is validated in Table 3, where it is shown that the unconditional distribution of hedge funds is far from the normal distribution.

A possible drawback of the stochastic dominance analysis conducted in Section 4 is that preserving the characteristics of the data may not control for the issue of returns smoothing. As stressed by Getmansky *et al*. (2004), hedge fund managers might invest in illiquid securities for which market prices are not readily available. In this case reported returns may be smoother than real economic returns. This leads to underestimation of the true return volatility and overestimation of hedge fund performance persistence. In a related work Stulz (2007) suggests that managers have discretion in the valuation of their assets under management. In other words, managers use performance smoothing to signal consistency and low risk profiles of their hedge funds. To test if serial autocorrelation in hedge funds returns is a source of performance we replicate the analysis in Table 4 and Table 5 testing the same hypotheses, but this time the performance measures are calculated using "unsmoothed" rather than the observed series of returns. Similarly, we also repeat the quantile regressions of table 6 using unsmoothed data. We do not report the results using unsmoothed data for the stochastic dominates tests for persistence shown in Table 5 and the quantile regressions reported in Table 6 as the results are unchanged.[10] The stochastic dominance tests examining whether hedge funds outperform the market are somewhat different however and deserve some additional attention.

[10] The results obtained n by repeating the analysis of tables 5 and 6 using unsmoothed data is available from the corresponding author upon request.

The approach we follow to unsmooth the observed returns is based on a variation of the methodology suggested by Geltner (1991); see also Marcato and Key (2007). Consider the observed value of a hedge fund $X_{i,t}$. A simple smoothing model can be based on a single exponential smoothing approach:

$$X_{i,t} = \alpha X_{i,t} + (1-\alpha)X^*_{i,t}, \tag{5}$$

where $X^*_{i,t}$ is the unobservable underlying hedge fund return at time *t* for the i^{th} hedge fund, and α (for $\alpha \in 0,1$) is the smoothing parameter. From Equation (5), the unsmoothed returns can be computed as follows

$$X^*_{i,t} = (1-\alpha)^{-1}\left(X_{i,t} - \alpha X_{i,t}\right). \tag{6}$$

Therefore, the unsmoothed returns were obtained using Equation (6) where the parameter α was estimated using the Kalman filter. Once the unsmoothed returns have been obtained the stochastic dominance tests and the quantile regressions were repeated.

Panels A, B and C in Table 7 repeat the results of the stochastic dominance test for superior performance of hedge funds over the S&P 500, Russel 2000 and MSCI indexes respectively using unsmoothed data. As in Table 4, for each panel, we test whether the fund of fund and all hedge funds first and second order dominate the candidate benchmark in columns three to six. As in Table 4, the *p*-values in Table 7 were obtained using the bootstrap method. However, the block bootstrap method described in the Appendix is not suitable for data that are not correlated. For this reason, the algorithm

used to calculate the empirical *p*-values is based on the wild bootstrap method (see for example Davidson and Flachaire, 2008).

<<insert Table 7 about here>>

Table 7 reports that by removing the serial correlation of the returns does not change our overall conclusions. Panels A, B and C in Table 7 shows very little evidence that hedge funds have outperformed the market. In only one instance, for the Sharpe ratio for the aggregation of all hedge funds, do we see evidence that hedge funds outperformed the S&P 500. In contrast, Table 4 reported that according to the Sharpe ratio, hedge funds outperformed the market regardless of how the market is defined. Meanwhile, Table 7, Panel B reports that hedge funds underperformed the Russel 2000 index whereas Table 4 reports that hedge funds outperformed the Russel 2000 index in these instances. Otherwise neither the null hypothesis $H_0^1: X_i \succ_{s:=2} Y_j$ nor $H_0^2: Y_j \succ_{s:=2} X_i$ can be rejected for all stock market benchmarks.

In any event, we conclude that despite the declining returns suffered by the hedge fund industry in recent years, the weight of evidence presented here suggests that the hedge fund industry did not underperform the market as least as defined by the S&P 500 and the emerging market MSCI index. This conclusion is consistent with Bali *et al.* (2013), who while not formally testing for stochastic dominance, find that the fund of fund hedge fund strategy does not outperform the S&P500 according to the MPPM.

7. Asset based factor models

Additional insights concerning the behavior of top and mediocre funds are generated by examining the structure of asset-based risk exposures. To accomplish this task, we

run the seven factor Fung and Hsieh (2004) model on the top and mediocre performing funds. In interpreting these results, the reader should note that the samples underlying the performance-based portfolios are not randomly selected being based on formation month performance, is narrower and is estimated over a different time than Fung and Hsieh (2004) so our results can look different.

Table 8 reports the results of the Fung and Hsieh (2004) model as applied to our data. The second column repeats Fung and Hsieh (2004) for the fund of fund TASS index regression reported in table 2 of their paper. The third column reports the regression for all the out of sample fund of fund data and columns four through seven reports the quantile regression results for the top and mediocre funds at the 25th, 50th and 75th quantiles respectively.

The R-square for all samples of our fund of fund data is lower than Fung and Hsieh (2004) and many risk factors significant in Fung and Hsieh (2004) are not significant in the more recent period. This could be due to the more turbulent market conditions that, as reported in Table 2, resulted in industry wide loses in 2002, 2008 and 2011 that perhaps inspired fund managers to seek less systematic risk exposure. While the lower quantiles of mediocre and top performing funds experience negative alpha, funds in the 50th and 75th quantiles still manage to obtain positive alpha. What seems to separate top from mediocre funds is their decision to accept significant loadings on a different set of risk factors. For example, top but not mediocre performing funds at the 75th quantile have positive factor loadings on the bond BONDTFF and Commodity tread factors COMTF while mediocre but not top fund at the 75th quantile have positive factor loadings on the small firm SML and 10-year treasury interest rate BMF factors. Similarly, comparing top funds at the 25thquantile with mediocre funds at the 75th quantile we see that top but not mediocre funds have a negative loading on credit

conditions yet unlike mediocre funds, top funds do not load significantly on the small firm SML and 10 year treasury interest rate BMF factors It is remarkable that the market equity S&P 500 factor is always highly significant for all subsets of the TASS data."

8. Conclusions

Despite the declining returns from hedge fund investment, our stochastic dominance tests find that hedge funds did not perform worse than the market. Unlike Capocci et al. (2005) and Slavutskaya (2013), we find evidence that the superior performance of top quintile hedge funds does persist according to the MPPM, but only for six months rather than for two or three years as reported by Boyson (2008), Gonzalez *et al*. (2015) and Ammann *et al*. (2013). It is important to note that these results hold under very general conditions as we do not assume i.i.d. distributed data and they apply even when the data is characterized by serial dependence and heteroscedasticity.

Holding alpha performance constant, we find evidence that that top funds accept a distinctly different risk profile than mediocre funds, suggesting that top funds follow strategies 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 excess returns on the Fama and French (1995) model augmented by momentum, momentum reversal and liquidity risk factors and by the seven factor Fung and Hsieh (2004) model. The Fung and Hsieh (2004) model finds that the risk profile of top quintile performing funds is distinctly different from mediocre quintile funds by accepting a different set of asset based systematic risks. The augmented Fama French (1995) model finds that 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 rather than anticipate 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 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 quantile have the same augmented Fama French (1995) risk profile as 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, holding alpha performance constant, superior performing hedge funds can be 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 but earn risk premiums by accepting market risk. Additionally, they seem able to exploit fleeting opportunities leading to momentum profits while closing losing strategies thereby avoiding momentum reversal.

Appendix

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.

1A. 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_1 first order stochastically dominates X_2 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.

2A. 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

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

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

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

and $\hat{D}_j^s(x; \hat{F}_j)$ is similarly defined. Linton *et al.* (2005) show that under suitable regularity conditions $\hat{\Lambda}$ converges to a functional of a Gaussian process. However, the asymptotic null distribution of $\hat{\Lambda}$ 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 Equation (A.1) 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 Equation (A.1) as

$$\widehat{\Lambda}^{*}=\min \sup_{x\in\mathbb{R}}\sqrt{N}\left[\widehat{D}_{i}^{s*}\left(x;\hat{F}_{i}\right)-\widehat{D}_{j}^{s*}\left(x;\hat{F}_{j}\right)\right] \qquad \text{(A.3)}$$

where

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

and

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

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

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

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 Equation (A.3) converges to Equation (A.1). 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

This 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* (i) are the manipulation proof performance measures of Goetzmann *et al.* (2007) with a risk aversion parameter of i = 2, 3, 6 and 8 respectively.

Strategy	Number	Assets	Age	Rf	RoR	SR	MPPM(2)	MPPM(3)	MPPM(6)	MPPM(8)
Convertible Arbitrage	124	$251.47	6.44	0.18	0.32	0.45	0.00	-0.02	-0.06	-0.08
Dedicated Short Bias	24	$25.73	6.05	0.17	-0.08	-0.06	-0.06	-0.07	-0.13	-0.16
Emerging Markets	417	$196.34	5.94	0.10	0.59	0.18	0.01	-0.01	-0.09	-0.14
Equity Market Neutral	182	$170.66	5.79	0.15	0.36	0.25	-0.02	-0.04	-0.05	-0.06
Event Driven	347	$375.06	6.67	0.15	0.48	0.30	0.03	0.02	0.00	-0.01
Fixed Income Arbitrage	114	$302.15	6.29	0.17	0.37	0.69	0.02	0.01	-0.02	-0.05
Fund of Funds	1273	$206.00	5.97	0.12	0.12	0.10	-0.01	-0.02	-0.03	-0.04
Global Macro	158	$550.54	5.89	0.13	0.42	-1.03	0.03	0.02	0.00	-0.02
Long/Short Equity Hedge	1265	$155.44	6.27	0.14	0.44	0.10	0.01	0.00	-0.04	-0.07
Managed Futures	295	$257.77	6.43	0.12	0.56	0.26	0.01	-0.01	-0.07	-0.11
Multi-Strategy	266	$437.17	5.86	0.12	0.43	0.23	0.02	0.01	-0.01	-0.03
Options Strategy	12	$92.53	7.70	0.13	0.55	0.48	0.03	0.02	0.01	0.00
Other	123	$273.05	5.74	0.11	0.60	0.41	0.03	0.02	-0.03	-0.05
Grand Total	4600	$238.48	6.14	0.13	0.37	0.15	0.01	0.00	-0.04	-0.06
Live Funds	1922	$256.67	6.27	0.08	0.45	0.20	0.02	0.01	-0.04	-0.06
Dead Funds	2678	$221.24	5.62	0.18	0.30	0.09	0.00	-0.01	-0.06	-0.08
First Half	2033	$223.80	5.17	0.23	0.74	0.22	0.04	0.03	0.00	-0.01
Second Half	2567	$246.31	6.32	0.08	0.19	0.11	-0.01	-0.02	-0.06	-0.08

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

This 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* (i) are the manipulation proof performance measures of Goetzmann *et al.* (2007) with a risk aversion parameter of i = 2, 3, 6 and 8 respectively.

Year	Number	Assets	Age	Rf	RoR	SR	MPPM(2)	MPPM(3)	MPPM(6)	MPPM(8)
2001	512	$147.72	4.42	0.31	0.25	0.13	-0.08	-0.10	-0.16	-0.20
2002	151	$156.68	4.80	0.13	-0.11	0.08	-0.02	-0.03	-0.07	-0.09
2003	246	$171.35	5.32	0.08	1.39	0.61	0.05	0.04	0.01	-0.01
2004	455	$223.09	5.09	0.10	0.80	0.44	0.08	0.07	0.05	0.04
2005	333	$253.57	5.15	0.25	0.71	0.29	0.04	0.03	0.02	0.00
2006	336	$271.30	5.57	0.39	0.93	0.36	0.06	0.06	0.04	0.03
2007	397	$314.81	5.86	0.38	0.85	0.32	0.05	0.05	0.04	0.02
2008	428	$309.20	5.99	0.14	-1.70	-0.38	-0.10	-0.12	-0.17	-0.20
2009	282	$225.02	6.41	0.01	1.45	0.31	-0.09	-0.12	-0.21	-0.26
2010	483	$225.39	6.68	0.01	0.87	0.34	0.10	0.09	0.06	0.04
2011	567	$207.16	6.30	0.00	-0.55	-0.13	0.03	0.02	-0.01	-0.03
2012	410	$207.62	6.62	0.00	0.46	0.24	-0.03	-0.04	-0.08	-0.11
Total	4600	$238.48	5.93	0.13	0.37	0.15	0.01	0.00	-0.04	-0.06

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

This 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 indices 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(8) are the manipulation proof performance measures of Goetzmann *et al.* (2007) with a risk aversion parameter of 2 and 8 respectively.

Statistic	**Rate of Return**					**Sharpe Ratio**				
	X_1	X_2	S&P	Russ	EMI	X_1	X_2	S&P	Russ	EMI
Mean	0.25	0.44	0.32	0.68	1.28	0.18	0.13	0.03	0.06	0.18
Median	0.57	0.66	1.00	1.63	1.28	0.26	0.29	0.20	0.22	0.19
St. Dev.	1.55	1.79	4.59	5.97	7.04	0.77	0.89	1.04	0.99	1.04
Skewness	-1.29	-0.84	-0.59	-0.51	-0.66	-0.47	-4.15	-0.63	-0.67	-0.49
Kurtosis	3.52	1.72	0.93	0.75	1.32	0.14	5.85	0.29	0.55	0.12
Min	-6.53	-6.47	-16.80	-20.80	-27.35	-2.16	-6.19	-3.44	-3.58	-2.95
20th Percentile	-0.79	-1.03	-2.51	-4.28	-3.32	-0.43	-0.27	-0.80	-0.81	-0.51
40th Percentile	0.15	0.19	0.06	0.05	-0.05	0.11	0.13	-0.04	-0.03	-0.02
60th Percentile	0.78	1.14	1.51	2.82	3.84	0.43	0.39	0.39	0.41	0.55
80th Percentile	1.48	1.78	3.72	5.32	7.14	0.86	0.66	0.89	0.89	1.01
Max	3.33	4.89	10.93	15.46	17.14	1.91	1.41	2.13	2.17	2.20
JB	41.56	27.00	34.15	36.61	27.44	54.49	3547.74	53.68	46.59	55.38
	MPPM(2)					**MPPM(8)**				
	X_1	X_2	S&P	Russ	EMI	X_1	X_2	S&P	Russ	EMI
Mean	-0.01	0.01	-0.02	0.01	0.05	-0.06	-0.06	-0.09	-0.12	-0.13
Median	0.02	0.03	0.00	0.04	0.14	-0.01	-0.01	0.01	-0.05	0.03
St. Dev.	0.08	0.10	0.08	0.22	0.32	0.14	0.14	0.25	0.29	0.44
Skewness	-1.40	-1.36	-1.22	-0.42	-0.96	-1.64	-1.64	-0.93	-0.88	-1.32
Kurtosis	1.88	3.15	1.36	0.16	0.89	3.02	3.02	0.24	0.71	1.53
Min	-0.27	-0.43	-0.29	-0.61	-0.92	-0.66	-0.66	-0.77	-0.93	-1.41
20th Percentile	-0.05	-0.05	-0.07	-0.16	-0.19	-0.14	-0.14	-0.31	-0.29	-0.39
40th Percentile	-0.01	0.00	-0.02	-0.03	0.07	-0.06	-0.06	-0.05	-0.17	-0.12
60th Percentile	0.03	0.05	0.03	0.08	0.18	0.01	0.01	0.04	0.01	0.08
80th Percentile	0.05	0.08	0.05	0.19	0.28	0.03	0.03	0.09	0.08	0.20
Max	0.12	0.18	0.11	0.48	0.62	0.12	0.12	0.37	0.44	0.56
JB	54.26	44.78	51.82	52.48	48.73	64.36	64.36	66.48	50.11	54.75

Table 4. Comparing hedge fund performance with the stock market

This table reports the first and second order stochastic dominance tests (s = 1 or 2 respectively) 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 Measure using a risk aversion parameter of 2, *MPPM*(2) 3, *MPPM*(3) and 8 *MPPM*(8). Panels A, B and C compare hedge funds to the *S&P* 500, *Russell* 2000 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:			*S&P 500*		
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
MPPM(8)	1	0.000	0.000	0.000	0.000
	2	0.537	0.234	0.678	0.504
Panel B			Russell 2000		
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
MPPM(8)	1	0.000	0.000	0.000	0.000
	2	0.995	0.003	0.538	0.001
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
MPPM(8)	1	0.000	0.000	0.000	0.000
	2	0.557	0.519	0.992	0.504

Table 5. Comparing top and mediocre hedge fund performance

This table reports the first and second order stochastic dominance tests (s = 1 or 2 respectively) to determine if the top (fifth) quintile Z_5 fund of fund X_1 and overall universe of US dollar hedge funds X_2 outperform the mediocre (third) quintile Z_3 for t months out of sample according to the Sharpe ratio and the Manipulation Proof Performance measure using a risk aversion parameter of 2, *MPPM*(2), 3, *MPPM*(3) and 8, *MPPM*(8).

		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*		
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)*		
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)*		
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
Panel D			*MPPM(8)*		
6	1	0.497	0.001	0.843	0.016
	2	0.997	0.000	0.999	0.000
12	1	0.178	0.999	0.627	0.392
	2	0.234	0.709	0.998	0.974
18	1	0.692	0.581	0.499	0.430
	2	0.515	0.326	0.864	0.635
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		$F_{t,5}$		$F_{t,3}$	
		Coefficient	**Bootstrap S.E.**	**Coefficient**	**Bootstrap S.E.**
Q25	*CONS*	-0.755**	0.287	-0.365**	0.189
	$MKTRF_t$	0.362***	0.085	0.277***	0.049
	SMB_t	0.150	0.159	0.054	0.054
	HML_t	0.067	0.190	0.114	0.089
	MOM_t	0.214***	0.072	0.075***	0.030
	LTR_t	-0.148	0.153	-0.205***	0.079
	$AGGLIQ_t$	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
	$MKTRF_t$	0.295***	0.083	0.236***	0.045
	SMB_t	0.037	0.100	0.058	0.053
	HML_t	-0.070	0.156	0.056	0.045
	MOM_t	0.130**	0.079	0.073***	0.022
	LTR_t	0.014	0.150	-0.118**	0.058
	$AGGLIQ_t$	-4.523	4.321	4.173*	2.095
	Pseudo R^2	0.131		0.320	
Q75	*CONS*	1.985***	0.325	0.779***	0.110
	$MKTRF_t$	0.281**	0.107	0.206***	0.037
	SMB_t	-0.009	0.119	0.049	0.049
	HML_t	-0.031	0.131	0.059	0.063
	MOM_t	0.150**	0.071	0.069**	0.032
	LTR_t	0.011	0.140	-0.033	0.052
	$AGGLIQ_t$	-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.

Table 7. Hedge fund performance and the market (unsmoothed returns).

This table reports the first and second order stochastic dominance tests (s = 1 or 2 respectively) 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 Measure using a risk aversion parameter of 2, *MPPM*(2), 3, *MPPM*(3) and 8 *MPPM*(8). Panels A, B and C compare hedge funds to the *S&P 500*, *Russell 2000* and the *MSCI* emerging market indices respectively. The hedge fund returns have been unsmoothed prior to the stochastic dominance analysis.

	s	$H_0^1: X_1 \succ_s Y_j$	$H_0^2: Y_j \succ_s X_1$	$H_0^1: X_2 \succ_s Y_j$	$H_0^2: Y_j \succ_s X_2$
			S&P 500		
Sharpe	1	0.000	0.000	0.000	0.001
	2	0.507	0.490	0.817	0.005
MPPM(2)	1	0.000	0.000	0.000	0.000
	2	0.789	0.453	0.539	0.389
*MPPM(*3)	1	0.000	0.000	0.000	0.000
	2	0.443	0.587	0.527	0.481
MPPM(8)	1	0.000	0.004	0.000	0.078
	2	0.999	0.587	0.999	0.567
			R2000		
Panel B					
Sharpe	1	0.000	0.000	0.000	0.004
	2	0.000	0.961	0.000	0.985
MPPM(2)	1	0.000	0.000	0.000	0.000
	2	0.000	0.673	0.004	0.459
MPPM(3)	1	0.000	0.000	0.000	0.000
	2	0.000	0.497	0.000	0.561
MPPM(8)	1	0.000	0.000	0.000	0.000
	2	0.000	0.456	0.507	0.493
Panel C			MSCI		
Sharpe	1	0.000	0.007	0.002	0.000
	2	0.546	0.385	0.932	0.489
MPPM(2)	1	0.000	0.000	0.000	0.000
	2	0.754	0.323	0.654	0.389
MPPM(3)	1	0.000	0.000	0.000	0.000
	2	0.477	0.489	0.507	0.493
MPPM(8)	1	0.000	0.000	0.000	0.000
	2	0.421	0.423	0.507	0.490

Table 8. Hedge fund performance and asset based risk factors (unsmoothed returns).

This table reports our estimate of Fung and Hsieh (2004) where the asset based risk factors are the bond $BONDTF_t$, foreign exchange $FXTF_t$ and commodity $COMTF_t$ trend factors and $SP500_t$,SML_t BMF_t and $CREDIT_t$ are the market, small firm, 10 year treasury rate and credit risk factors respectively. The second column repeats Fung and Hsieh (2004), table 2 for the TASS index and the third column reports the estimates of the same model for all of our out of sample data. The remaining columns reports the quantile regression estimates of Fung and Hsieh (2004) for top and mediocre performing funds at the 25th, 50th and 75th quantile respectively.

Factors	*Fung and Hsieh (1994-2002)*	*All TASS Fund of Fund Data (2001-2012)*	*Top Funds 25th*	*Mediocre Funds 25th*	*Top Funds 50th*	*Mediocre Funds 50th*	*Top Funds 75th*	*Mediocre Funds 75th*
CONS	0.00780***	0.208*	-0.920***	-0.426**	0.461**	0.514***	1.499***	0.973***
$BONDTF_t$	-1.06047**	-0.876	0.793	-0.730	0.443**	-0.414	0.414***	-0.280
$FXTTF_t$	0.01238***	0.243	0.937	0.420	1.078	1.499**	0.228	0.570
$COMTF_t$	0.02067	0.529	0.690	0.203	0.405	0.326	2.384*	-0.186
SP500t	0.29167***	1.522***	1.654**	1.138**	1.877***	1.082***	2.110***	1.54***
SMLt	0.25882***	2.0848*	1.361	0.680	1.325*	1.394***	0.564	0.840**
BMFt	-0.00417	-0.607	0.420	-0.710	-0.123	0.037	0.988	0.908**
CREDITTSF	-1.60482	-2.061***	-0.439**	-1.360**	-0.2995***	-0.631	-1.351	-0.896
R-Square %	0.73	0.456	0.248	0.272	0.243	0.238	0.263	0.276

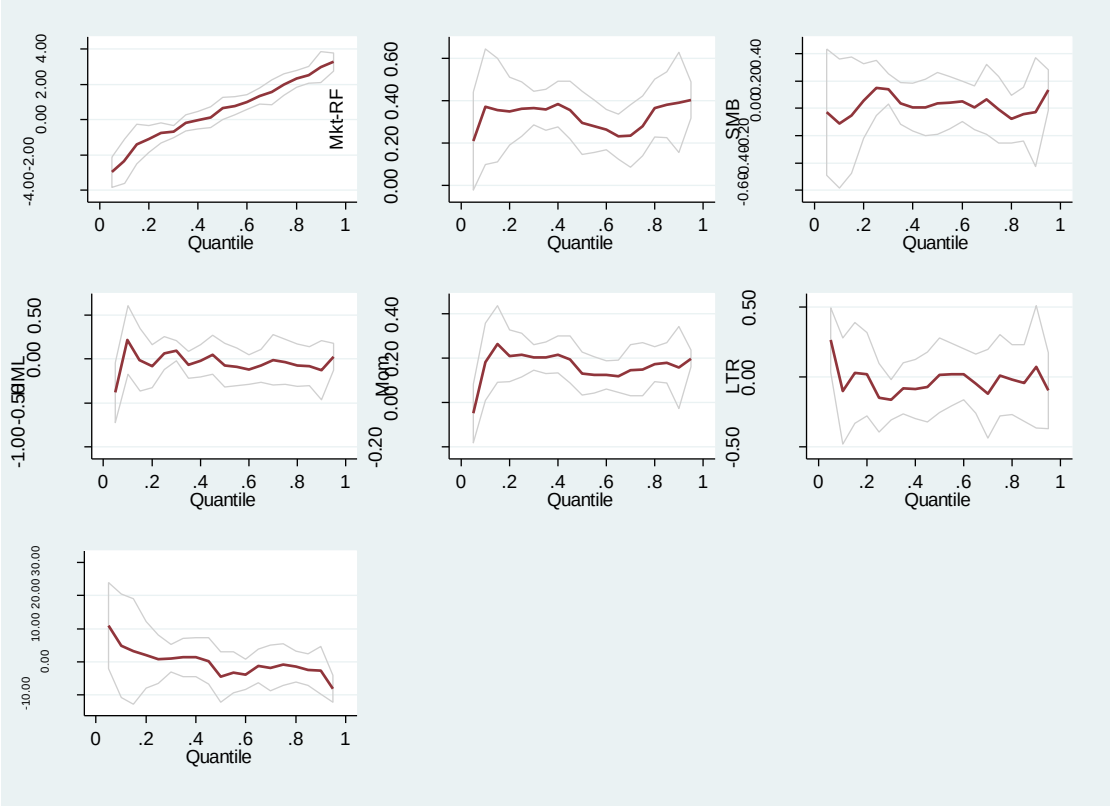

Figure 1. Marginal effects of risk factors on excess returns for top performing funds.

Each graph in the above figure depicts the relation between the size and the significance of the coefficient and the quantile of a given risk factor for top performing funds as measured by the manipulation proof performance measure with a risk aversion parameter of 3. The thinner lines depict the 5% upper and 95% lower confidence bounds. The risk factors are the market excess rate of return (*MKTRF*) and the size (*SMB*), growth (*HML*), momentum (*MOM*), momentum reversal (*LTR*) and liquidity (*AGGLIQ*) factors.

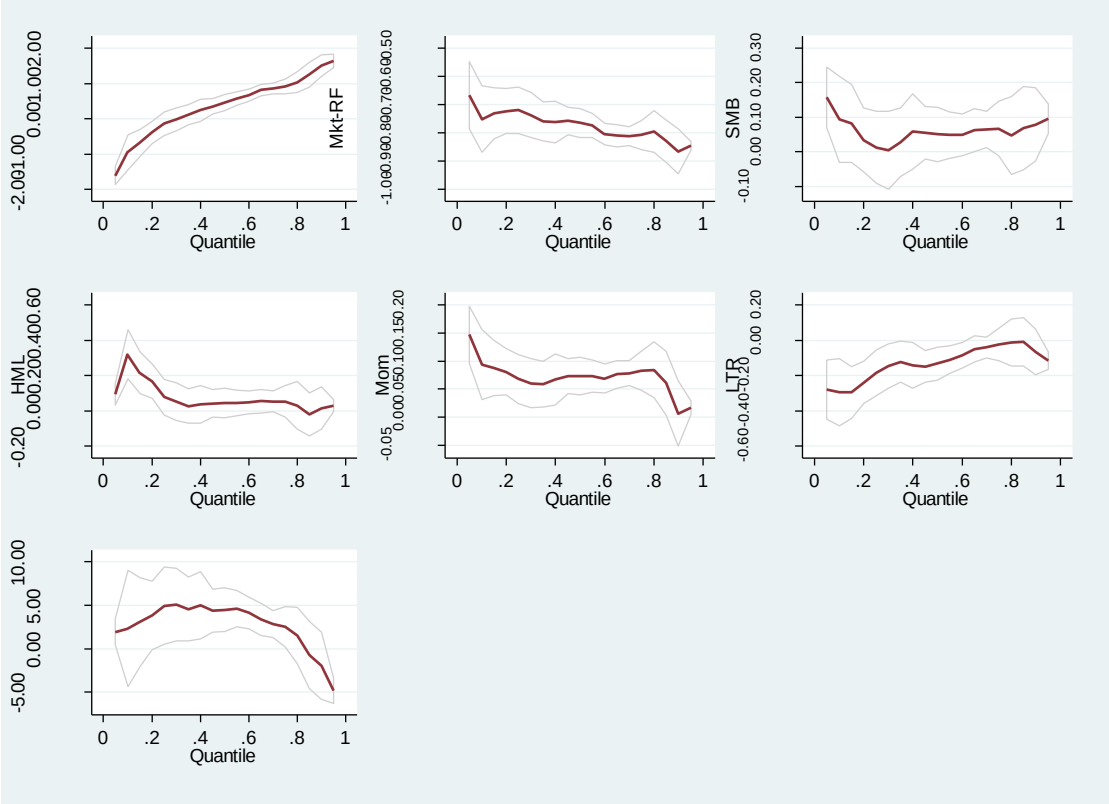

Figure 2. Marginal effects of risk factors on excess returns for mediocre performing funds. Each graph in the above figure depicts the relation between the size and the significance of the coefficient and the quantile of a given risk factor for mediocre performing funds as measured by the manipulation proof performance measure with a risk aversion parameter of 3. The thinner lines depict the 5% upper and 95% lower confidence bounds. The risk factors are the market excess rate of return (*MKTRF*) and the size (*SMB*), growth (*HML*), momentum (*MOM*), momentum reversal (*LTR*) and liquidity (*AGGLIQ*) factors.

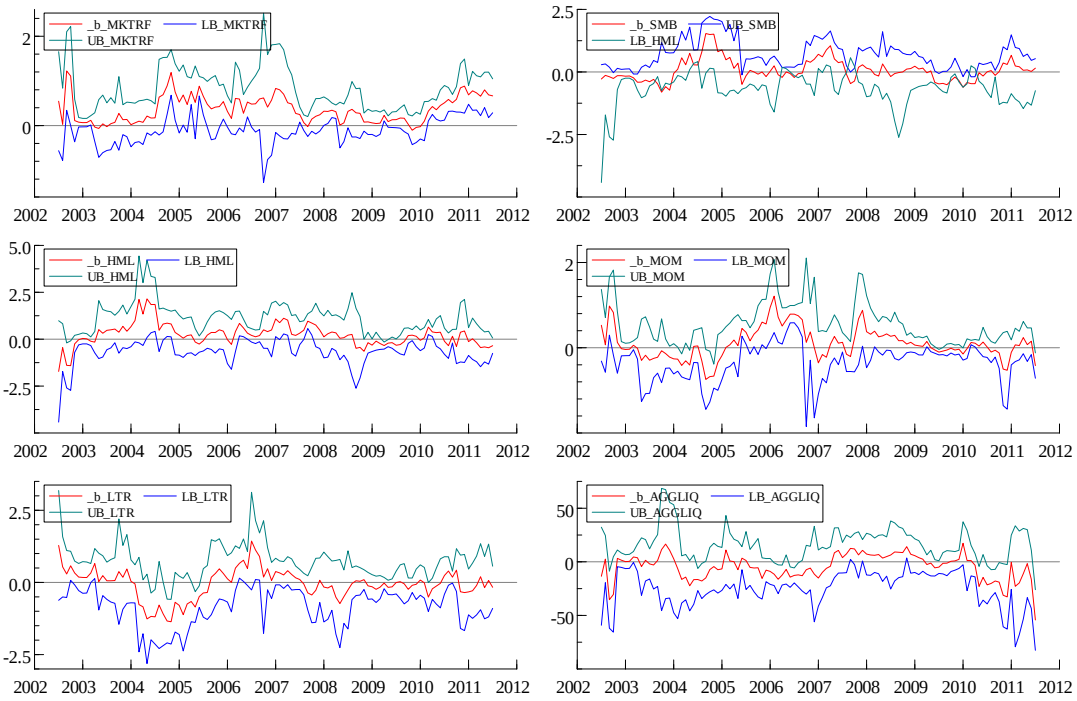

Figure 3. Time variation of the risk factors for top performing funds

Using a 12 month rolling window, 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.

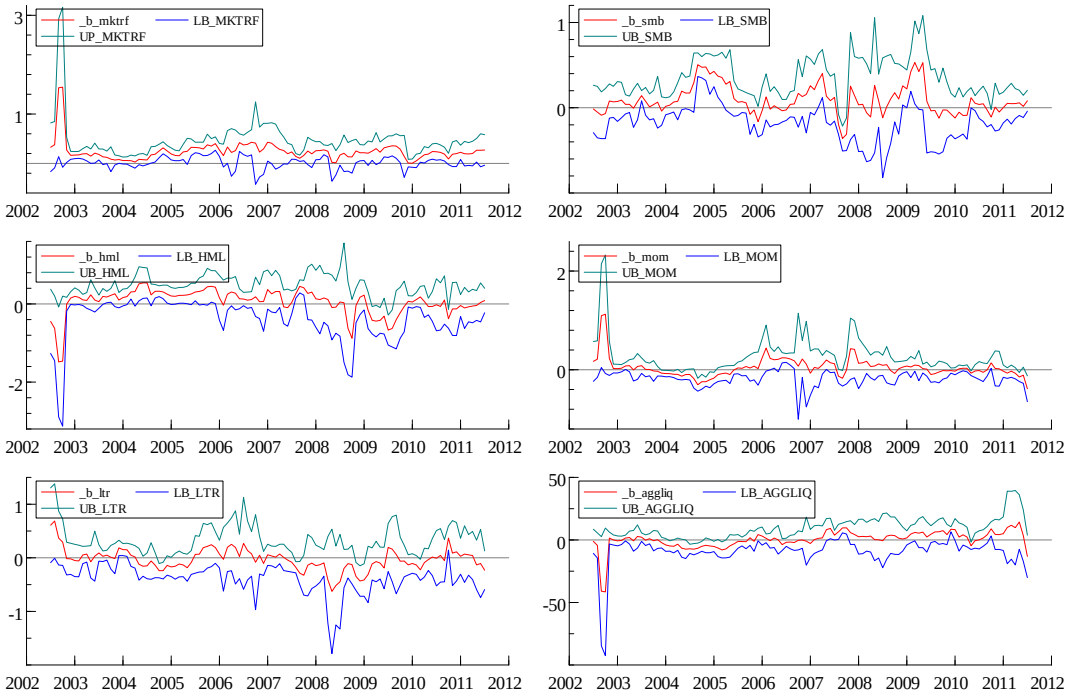

Figure 4. Time variation of the risk factors for mediocre performing funds

Using a 12 month rolling window, 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.