Hedge Fund Strategies: A non-Parametric Analysis*

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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 fewer risk factors that mostly anticipate the troubling economic conditions prevailing after 2006. Holding alpha performance constant, top performing funds mostly 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 $2.9 trillion of assets under management as of December 2018.[1] Yet, due to the light regulatory nature of the industry, we know 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 fund characteristics (Boyson (2008), the sex of managers (Aggarwal and Boyson 2016) or the fee structures (Aggarwal *et al*. 2009) of hedge funds, see El Kalak *et al*. (2016b) for a review of managerial characteristics of hedge funds and see El Kalak *et al*. (2016a) for a review of hedge fund risk management practices. 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. This paper's aims are consistent with Stafylas *et al*. (2018) who look at hedge fund behaviour by hedge fund style under different market conditions. Our paper is different however as we look at changes in aggregate hedge fund behaviour according to verified performance level as we move through the difficult market conditions associated with the 2007 liquidity crisis and the 2008-09 recession.

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 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

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

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.

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. 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 which assume hedge fund returns are i.i.d., we use non-parametric techniques that allow us to conduct formal statistical tests that are robust to serial and cross dependence among hedge funds return distributions. 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 *et al*. (2005). The authors 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, 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 use an inference procedure that 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 heteroscedasticity.

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 at least 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. 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 acknowledged 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 characteristics 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 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 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 performed as well as 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. 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 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 do this for funds of verified 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. Specifically, the excess returns of top performing funds are significantly related to the market premium and momentum across a broad range of quantiles and only for the top quintal, liquidity and lookback volatility. In contrast, the excess returns for mediocre funds are also related to many other factors across a broad range of quantiles including not only the market premium and momentum, but also the SMB and HML Fama French factors. Moreover, unlike top performing funds, liquidity is a significant factor for a broader range of quantiles for mediocre performing funds. Interestingly, momentum reversal is significantly negative for the lowest quantile of mediocre performing funds suggesting that one reason why mediocre funds do less well than top funds is that they are slow to close out a losing strategy.

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 and for the momentum factors, factors that are significant throughout a broad range of quintiles for top performing funds, 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. Meanwhile for mediocre performing funds, the confidence envelops for market risk and momentum factors also widen in 2006 but unlike top performing funds, the confidence envelope does not narrow during the financial crisis. Moreover, for third quintile performing funds, the dispersion of coefficient values for other significant factors, such as SMB and HML increase before and continue during the 2008 recession. This suggests that the market and the momentum factors, factors that are significant in explaining top fund performance, anticipate the liquidity crisis and subsequent recession whereas the factors that significantly explain mediocre hedge fund performance, do not fully anticipate the liquidity crisis and subsequent recession and merely react to coincident events.

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. Moreover, 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. 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 more risk factors than top performing funds that appear to react rather than anticipate future economic events..

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. Section 7 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 large 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.

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. Moreover, Bali (2013) finds that traditional mean variance measures (e,g. Sharpe and Traynor ratios) and downside adjusted risk measures (e.g. VAR and Sortino ratios) "does not generate a robust, consistent ranking among hedge fund strategy's". Goetzmann *et al.* (2007) point out that common performance measures such as the Sharpe 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. According to Brown *et al.* (2010) the MPPM is more correct than other measures, including measures that are designed to incorporate tail risk such as the Sortino and the VAR approaches. Still, Billio et al. (2013) discover that the MPPM measure, especially when using lower risk aversion parameters, is 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, and to provide a performance measure resistance to manipulation that Brown *et al.* (2010) suggests is the most accurate, we compile MPPM statistics using a broad range of risk aversion parameters.

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.* (2016) 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 *et al.* (2010) find performance persistence only for top 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. 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.* (2016) 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.

A final strand of the literature examines the structure of risk factors that explains hedge fund returns. Titman and Tiu (2011) 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, Boyson *et al.* (2010) find evidence of hedge fund contagion that they attribute to liquidity shocks while Stafylas *et al*. (2018) find that different risk factors are operative under different market conditions. Chen and Liang (2007) find evidence that market timing hedge funds can time the market for anticipated changes in volatility, returns and their combination while Cao *et al*. (2013) find that mutual fund managers can time the market for anticipated changes in liquidity. Bali *et al.* (2014) show that a substantial proportion of the variation in hedge fund returns can be explained by several macroeconomic risk factors.

In summary we find that we do not know much about how top performing hedge funds add value when compared to mediocre performing hedge funds. What is clear however, is that performance persistence and liquidity can influence hedge fund returns. It is an unresolved question as to whether top as opposed to modestly performing funds respond to these influences in the same way.

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 and the traded 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 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 instant history 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 *et al.* 2014, online Appendix 1). Accordingly, we follow, Aggarwal and Jorion (2010), Bali (2013, 2014) and delete the first 12 months of this data to adjust for instant history bias and the remaining 24 data points are used to calculate the starting values of the MPPM. 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.[3] 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 manipulation proof performance measure of Goetzmann *et al.* (2007) as reported below where $t = 1, \dots, T$ 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.

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

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. Billio *at al.* (2013) find that the MPPM measure is 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 likely 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 and 8.

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 *et al*. (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 to find the same results we report below using Linton *et al*. (2005) on the TASS reported data.

[3] 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.

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).

<<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 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” and “mediocre” funds and are less interested in examining strategies by style partly because this issue has been well examined by Stafylas *et al*. (2018). 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 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. For each month, we separate the sample by quintile and then hold these portfolios for the subsequent 24 months calculating the MPPM measures for each out of sample month. Therefore, we construct 2,880 portfolios each for the top and mediocre performing funds to examine the behavior of hedge funds by performance level as we enter and move through the 2007-08 financial crisis.

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. 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.

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 and X_2 denote 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[4] is as follows:

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

i) $E[u(X_1)] \geq E[u(X_2)]$

[4] See Levy (1992) for more details on the definition of first and second order stochastic dominance.

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 for stochastic dominance is based on comparing (functions of) the cumulate distributions of the hedge funds and stock market indexes. 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. We chose to use Linton *et al.* (2005) as it represents an important breakthrough in this literature 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. Below, we first briefly define the criteria of stochastic dominance and we then describe the testing procedure for stochastic dominance adopted in the paper.

4.1. 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

$$\widehat{\Lambda} = \min \sup_{x \in \mathbb{R}} \sqrt{N}\left[\widehat{D}_i^s\left(x; \widehat{F}_i\right) - \widehat{D}_j^s\left(x; \widehat{F}_j\right)\right], \tag{2}$$

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

$$\widehat{D}_i^s\left(x; \widehat{F}_i\right) = \frac{1}{N(s-1)!} \sum_{t=1}^{T} 1\left(X_{i,t} \leq x\right)(x - X_{i.t})^{s-1}, \tag{3}$$

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 Equation (2) 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 (2) as

$$\widehat{\Lambda}^{*}=\min \sup_{x\in\mathbb{R}}\sqrt{N}\left[\widehat{D}_{i}^{s*}(x;\widehat{F}_{i})-\widehat{D}_{j}^{s*}(x;\widehat{F}_{j})\right] \qquad (4)$$

where

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

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

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

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 (4) converges to Equation (2). Also, asymptotic theory requires that $b\to\infty$ and $b/N\to 0$ as $N\to\infty$.

4.2. 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 the MPPM of Goetzmann *et al.* (2007). We chose the MPPM as Brown *et al.* (2010) suggests is the most accurate performance measure. Bali (2013) finds that a broad range of traditional mean variance performance measures (e,g. Sharpe and Traynor ratios) and downside adjusted risk measures (e.g. VAR and Sortino ratios) are not robust as they provide inconsistent rankings of performance whereas the MPPM does not have this issue. We calculate the MPPM using a broad range of risk aversion parameters (A = 2, 3, 8) in response to Billio et al. (2013).

For each hedge portfolio, we test to determine if the returns first or second order stochastically dominate, or the reverse, three market indexes. The essence of our test strategy is as follows. Let X_i be the performance of the hedge fund portfolio i (for $\boldsymbol{i} = 1,2; fund\ of\ funds, all\ hedge\ funds$) and let Y_j denote the performance of the stock market index j (for $j = 1, \dots, 3; S\&P500, Russell\ 2000, MSCI$). 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.

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 $H_0^1\colon X_1 \succ_s Y_j$ the fund of fund portfolio stochastically dominates the j market index at s order, whereas under $H_0^2\colon Y_j \succ_s X_1$ the opposite is true. 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. 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, neither the null hypothesis $H_0^1\colon X_i \succ_{s:=2} Y_j$ nor $H_0^2\colon Y_j \succ_{s:=2} X_i$ can be rejected for the S&P 500 and MSCI stock market benchmarks. Therefore, the stochastic dominance test is inconclusive. However, the test results are different in Panel B for the Russel 2000 benchmark. Here we see that the hypothesis $H_0^1\colon X_i \succ_{s:=2} Y_j$ cannot be rejected so evidently hedge funds outperformed the small cap dominated Russel 2000 index. 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 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 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.[5]

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). 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 $\Theta = \{Z_k : z_k | \delta,\ Z_k \subseteq X_i , k \in \{1, \ldots, 5\}\}$. We

[5] See Gonzalez *et al.* (2016) for a detailed explanation.

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

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

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 three 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 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>>

Table 5 reports that the dominance tests 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. This discovery of shorter-term persistence is consistent with Agarwal and Naik (2000). Therefore, unlike Slavutskaya (2013), we do find some evidence of performance persistence for top funds but performance persistence is much more modest than found by Gonzalez *et al.* (2016), 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.

The asset pricing literature is dominated by the APT and extended CAPM approaches where no one approach dominates. For hedge funds, Fung and Hsieh (2004) seminal paper identifies a seven-factor systematic risk factor model. CAPM has been extended several times to accommodate various anomalies. Fama and French (1995) add a size and a value factor to CAPM while Carhart (1997) adds momentum and Pastor and Stambaugh (2003) adds liquidity to Fama French (1995). More recently, Fama and French (2015) add two additional factors for profitability and investment factors to the Fama French (1995) three factor model.

Our literature review reveals that liquidity (see Aragon 2007, Boyson et al. 2010**,** Sadka 2010, 2012) and persistence influence hedge fund returns. Persistence could be a result of momentum, so we think it is interesting to see if the reliance of hedge funds on momentum and liquidity is the same by performance level. Therefore, we use Carhart's (1997) momentum augmented Fama French (1995) model and include momentum reversal and Pastor and Stambaugh's (2003) traded liquidity factor as prior research suggests that liquidity and momentum are likely to be other market priced risk factors.[6] To account for the option like payoffs that are prevalent for hedge funds (see Fung and Hsieh 2001, 2004 and Page and Panariello 2018) we include the first principal component of the five categories of lookback straddle returns of Fung and Hsieh (2001).Therefore, we explain out of sample net excess returns of top and mediocre performing hedge funds by quintile for the fund of fund sector using a parsimonious extension of Carhart (1997).[7] Accordingly, 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 ($MKTRF_t$), size (SMB_t), value (HML_t), momentum (MOM_t), momentum reversal (LTR_t), liquidity ($TRADELIQ_t$) and volatility ($LOOKBACK_t$).

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:

$$F_{t,k} = f(MKTRF_t, SMB_t, HML_t, MOM_t, LTR_t, TRADELIQ_t, LOOKBACK_t). \quad (5)$$

We estimate Equation (5) using the quantile regression method. Quantile regression is a procedure for estimating a functional relationship between the response variable and the

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6 It has been suggested that we look at Fung and Hsieh (2004) too. The results are problematic however as our portfolios, being selected according to performance level rather than by random selection, may not be well diversified. Moreover, Fung and Hsieh (2004) type models are most informative when analysing the behaviour of hedge funds by style rather than by performance level. An analysis of hedge fund by style is provided by Stafylas *et al.* (2018).

7 For the sake of robustness, we also estimate the model using the data for all hedge funds and obtain similar results. We also estimate a less parsimonious model by including the profitability and investment factors of Fama French (2015) and find that these additional factors are not significant. This may be due to the correlation between factors and/or to their time-varying dimensions. Racicot and Theoret (2013) find that the hedge fund exposure to these factors may change substantially over the business cycle.

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 (5) 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 (5) 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 (5) can be specified as

$$Q(\tau \mid R_t = r) = R'_t \beta(\tau), \qquad \text{for } 0 \leq \tau \leq 1 \qquad (6)$$

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 (5) and β is a vector of coefficients to be estimated. In Equation (6) the τ-quantile is expressed as the solution of the optimization problem

$$\hat{\beta}\,(\tau) = argmin \sum_{i=1}^{n} \rho_\tau\left(F_{t,k} - R_t{}'\beta\right) \qquad (7)$$

where $\rho_\tau(\xi) = \xi\left(\tau - I(\xi < 0)\right)$ and $I(\cdot)$ is an indicator function. Equation (7) 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.

The estimation method used to find the solution of the minimization problem in Equation (7) is the GMM-based robust instrumental variables technique (see Le Yu and Sokbae, 2018). As highlighted by Racicot and Rentz (2015) (see also Racicot and Rentz, 2016 and the references therein) it is important to account for the presence of measurement errors and endogeneity that may lead to an inconsistent estimation when the ordinary least squares method is applied to a Fama and French-type model. Recent research has highlighted that liquidity, for example, may endogenously reveal itself during a period of financial turmoil (see Adrian *et al*., 2017). In this respect using instrumental quantile regression methods address the endogeneity issue delivering consistent estimators in Equation (7).

Table 6 reports the quantile regression estimates of Equation (6) for the top $\mathrm{F}_{t,5}$ and mediocre $\mathrm{F}_{t,3}$ performing portfolio excess returns six months out of sample. This table has three panels reporting the estimates of Equation (6) at the 25th, 50th and 75th quantiles. In column three, the estimated coefficients for Equation (6) for the top quintile of performing funds $\mathrm{F}_{t,5}$ are reported, whereas column five reports the estimates for the mediocre performing funds $\mathrm{F}_{t,3}$. 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 (6) 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 consistently significant for top performing funds, whereas mediocre performing funds have at least five 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 statistically significant liquidity, SMB, HML factors at all three quantiles. This clearly suggests that mediocre funds accept more sources of systematic risk than top performing funds. Moreover, replying on illiquid assets to achieve performance is a prevalent feature of mediocre performing funds whereas this is a significant factor for top performing funds only at the highest 75^{th} quintile. The volatility factor is significant only for top performing funds at the higher 75^{th} quintile suggesting that only the top performers can benefit from volatility. Interestingly, the momentum reversal factor is significantly negative for the lower 25^{th} quintile of mediocre performing funds implying that these 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 at the 25^{th} quintile, mediocre funds do not quickly change their strategy when it starts to fail.

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 boundaries of the shaded area indicate 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. Looking at TRADEDLIQ and LOOKBACK factors we see that these coefficients become positive from about the 60th percentile and higher.

<<Figures 1 and 2 about here>>

Looking at Figure 2, we see that mediocre performing funds F_3, behave like top performing funds F_5,in that the MKTRF and MOM factors are always positive and except for MOM at the extreme quantiles, statistically significant. The three additional factors significant for mediocre funds, SMB, HML and TRADELIQ are positive and statistically significant throughout a broad range of quantiles where the coefficients SMB and HML tend to decline and become less significant for the highest quantiles. Meanwhile, LTR clear rises by quantile from negative and significant for quantiles below 0.4 to positive but insignificant at the higher quantiles suggesting that one reason why mediocre performing funds perform less well is their inability to close out losing positions in a timely manner. In contrast, Figure 1 reveals that top performing funds never have a statistically significant LTR at any quantile.

Finally, we estimate the time varying coefficients for Equation (6). 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 Equation (6).

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 (6) 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. For top performing funds, Figure 3 shows that the confidence envelope of the market risk and the momentum factors widen in 2006 and early 2007 and then subsequently narrow suggesting that these risk factors were subject to greater uncertainty in the run up to the recent financial crisis. Meanwhile for mediocre performing funds, Figure 4 shows that the confidence envelops for market risk and momentum factors also widen in 2006 but unlike top performing funds, the confidence envelope does not narrow during the financial crisis. Meanwhile, the confidence envelops for the SMB and HML factors for mediocre performing funds also widen prior to the financial crisis period but remain wide during the 2008 recession. The confidence envelope for liquidity widens and the coefficient turns negative during the 2007 liquidity crisis. 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 are coincident with systematic risk, reacting rather than anticipating growing economic uncertainty. While 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 underestimating true return volatility and overestimating 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 dominance tests for persistence shown in Table 5 and the quantile regressions reported in Table 6 as the results are unchanged.[8] The stochastic dominance tests examining whether hedge funds outperform the market are somewhat different however and deserve some additional attention.

The approach we follow to unsmooth the observed returns is based on the methodology suggested by Getmansky *et al*. (2004). The method assumes that the observed return in period t (X_t) is a weighted average of the "true" returns, X_t^*, over the most recent ξ +1 periods, including the current period:

$$X_t = \theta_0 X_t^* + \theta_1 X_{t-1}^* + \cdots + \theta_\zeta X_{t-\zeta}^*,$$

with two conditions

$$\theta_\gamma \in [0,1],\ \gamma = 0, \dots, \zeta,$$

$$1 = \theta_0 + \theta_1 + \cdots + \theta_\zeta.$$

The parameter θ can be estimated by maximum likelihood. Once the parameters θ_γ have been estimated, the "true" return X_t^* is obtained by calculating

$$X_t^* = \frac{X_t - \theta_1 X_{t-1}^* - \cdots - \theta_\zeta X_{t-\zeta}^*}{\theta_0}. \quad (8)$$

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

A recurring application of the formula in Equation (8) on the observed returns provides a series of corrected returns which is free of serial correlation (see Getmansky *et al*., 2004 for more details).

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 Section 4 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>>

Panels A, B and C in Table 7 shows very little evidence that hedge funds have outperformed the market. In fact, we find that the market, as defined by the small cap dominated Russel 2000 index outperforms rather than underperforms hedge funds. This suggests that our earlier finding that hedge finds outperform the small cap dominated Russel 2000 index could be an artifact of return smoothing. Meanwhile the results for the S&P500 and the MSCI indexes in Table 7 are, like those for the smoothed data of Table 4, inconclusive.

In any event, 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 performed as well as the market. This conclusion is consistent with Bali *et al.* (2013) who find that the fund of fund hedge fund strategy does not outperform the S&P500 according to the MPPM.

7. 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*. (2016) 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 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 Carhart (1997) model augmented by momentum reversal, traded liquidity risk and volatility. The augmented Carhart (1997) 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 that appear to anticipate growing economic risk. However, excess returns for mediocre performing funds are, in addition to market risk and momentum factors, significantly associated with three other factors, the SMB and HML Fama French factors as well as liquidity, 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 at the lower quantiles of mediocre performing funds, 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 top performing funds at the 75th quantile are also significantly associated with liquidity and volatility risks, hinting that the very best of the top performing funds could be successfully following a more refined strategy explaining why these funds are the very best performers.

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 earn risk premiums by accepting fewer sources of systematic risks that anticipate growing risks.

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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. *MPPM* (A)* are the manipulation proof performance measures of Goetzmann *et al.* (2007) with a risk aversion parameter of A = 2, 3 and 8 respectively. Assets are in millions, age is in years and the risk-free rate Rf, the rate of return RoR and the three manipulation proof performance measures are in percent.

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

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

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

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. *MPPM* (A)* are the manipulation proof performance measures of Goetzmann *et al.* (2007) with a risk aversion parameter of A = 2, 3 and 8 respectively. Assets are in millions, age is in years and the risk-free rate Rf, the rate of return RoR and the three manipulation proof performance measures are in percent.

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

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

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

Table 3. Monthly average characteristics of the performance measures

This table reports the mean, median, standard deviation, skewness, excess 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 (S&P), Russell 2000 (RUSS) and MSCI (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. MPPM(2), MPPM(3) and MPPM(8) are the manipulation proof performance measures MPPM* of Goetzmann *et al.* (2007) with a risk aversion parameter of 2, 3 and 8 respectively. All data is in percent.

Statistic	**Rate of Return**					**MPPM(2)**				
	X_1	X_2	S&P	Russ	EMI	X_1	X_2	S&P	Russ	MSCI
Mean	0.25	0.44	0.32	0.68	1.28	-0.01	0.01	-0.02	0.01	0.05
Median	0.57	0.66	1.00	1.63	1.28	0.02	0.03	0.00	0.04	0.14
St. Dev.	1.55	1.79	4.59	5.97	7.04	0.08	0.10	0.08	0.22	0.32
Skewness	-1.29	-0.84	-0.59	-0.51	-0.66	-1.40	-1.36	-1.22	-0.42	-0.96
Excess Kurt	3.52	1.72	0.93	0.75	1.32	1.88	3.15	1.36	0.16	0.89
Min	-6.53	-6.47	-16.80	-20.80	-27.35	-0.27	-0.43	-0.29	-0.61	-0.92
20th Percentile	-0.79	-1.03	-2.51	-4.28	-3.32	-0.05	-0.05	-0.07	-0.16	-0.19
40th Percentile	0.15	0.19	0.06	0.05	-0.05	-0.01	0.00	-0.02	-0.03	0.07
60th Percentile	0.78	1.14	1.51	2.82	3.84	0.03	0.05	0.03	0.08	0.18
80th Percentile	1.48	1.78	3.72	5.32	7.14	0.05	0.08	0.05	0.19	0.28
Max	3.33	4.89	10.93	15.46	17.14	0.12	0.18	0.11	0.48	0.62
JB	41.56	27.00	34.15	36.61	27.44	54.26	44.78	51.82	52.48	48.73
	MPPM(3)					**MPPM(8)**				
	X_1	X_2	S&P	Russ	EMI	X_1	X_2	S&P	Russ	EMI
Mean	0.01	0.05	-0.01	-0.03	0.02	-0.06	-0.06	-0.09	-0.12	-0.13
Median	0.04	0.14	0.03	0.05	0.12	-0.01	-0.01	0.01	-0.05	0.03
St. Dev.	0.22	0.32	0.23	0.21	0.34	0.14	0.14	0.25	0.29	0.44
Skewness	-0.42	-0.96	-0.50	-0.79	-1.01	-1.64	-1.64	-0.93	-0.88	-1.32
Kurtosis	0.16	0.89	0.24	0.13	0.94	3.02	3.02	0.24	0.71	1.53
Min	-0.61	-0.92	-0.66	-0.63	-0.99	-0.66	-0.66	-0.77	-0.93	-1.41
20th Percentile	-0.16	-0.19	-0.19	-0.23	-0.21	-0.14	-0.14	-0.31	-0.29	-0.39
40th Percentile	-0.03	0.07	-0.05	0.02	0.02	-0.06	-0.06	-0.05	-0.17	-0.12
60th Percentile	0.08	0.18	0.06	0.06	0.16	0.01	0.01	0.04	0.01	0.08
80th Percentile	0.19	0.28	0.17	0.13	0.26	0.03	0.03	0.09	0.08	0.20
Max	0.48	0.62	0.47	0.41	0.60	0.12	0.12	0.37	0.44	0.56
JB	52.48	48.73	51.90	64.31	50.02	64.36	64.36	66.48	50.11	54.75

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

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 Manipulation Proof Performance Measure MPPM* 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*		
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		
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		
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

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

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 manipulation proof performance measure MPPM* 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		*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

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

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*), liquidity (*TRADELIQ*) and lookback straddles returns (*LOOKBACK).*

Quantile		$F_{t,5}$		$F_{t,3}$	
		Coefficient	**S.E.**	**Coefficient**	**S.E.**
Q25	*CONS*	-0.589**	0.314	-0.606***	0.129
	$MKTRF_t$	0.374***	0.080	0.256***	0.032
	SMB_t	0.140	0.131	0.065***	0.021
	HML_t	0.020	0.136	0.174***	0.055
	MOM_t	0.208***	0.062	0.087***	0.025
	LTR_t	-0.128	0.152	-0.209***	0.062
	$TRADELIQ_t$	-1.810	1.756	4.062***	1.244
	$LOOKBACK_t$	0.406	0.314	-0.147	0.126
	R^2	0.225		0.390	
Q50	*CONS*	-0.949***	0.304	0.266**	0.134
	$MKTRF_t$	0.239***	0.077	0.185***	0.034
	SMB_t	-0.215	0.127	0.105**	0.036
	HML_t	0.010	0.132	0.012**	0.005
	MOM_t	0.109*	0.061	0.064**	0.026
	LTR_t	-0.059	0.148	-0.081	0.065
	$TRADELIQ_t$	-1.584	1.720	2.413***	0.388
	$LOOKBACK_t$	0.308	0.300	-0.027	0.132
	R^2	0.147		0.280	
Q75	*CONS*	2.080***	0.180	0.863***	0.107
	$MKTRF_t$	0.269***	0.046	0.197***	0.027
	SMB_t	-0.004	0.075	0.089**	0.045
	HML_t	-0.033	0.078	0.044**	0.026
	MOM_t	0.088**	0.036	0.049**	0.021
	LTR_t	0.007	0.087	-0.006	0.052
	$TRADELIQ_t$	4.640**	1.576	2.432**	0.729
	$LOOKBACK_t$	0.619***	0.178	0.123	0.106
	R^2	0.206		0.270	

***,**,* statistically significant at the 1, 5 and 10% level respectively. SE are the estimated standard errors.

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 manipulation proof performance measure MPPM 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	$H_0^1: X_1 \succ_s Y_j$	$H_0^2: Y_j \succ_s X_1$	$H_0^1: X_2 \succ_s Y_j$	$H_0^2: Y_j \succ_s X_2$
Panel A			S&P 500		
MPPM(2)	1	0.000	0.000	0.002	0.000
	2	0.892	0.423	0.336	0.491
MPPM(3)	1	0.000	0.003	0.000	0.000
	2	0.343	0.561	0.226	0.513
MPPM(8)	1	0.000	0.000	0.000	0.009
	2	0.951	0.471	0.999	0.487
Panel B			R2000		
MPPM(2)	1	0.000	0.000	0.000	0.000
	2	0.000	0.515	0.000	0.551
MPPM(3)	1	0.000	0.000	0.000	0.000
	2	0.000	0.787	0.000	0.531
MPPM(8)	1	0.000	0.002	0.000	0.000
	2	0.000	0.479	0.507	0.471
Panel C			MSCI		
MPPM(2)	1	0.000	0.000	0.000	0.000
	2	0.467	0.591	0.724	0.496
MPPM(3)	1	0.000	0.000	0.000	0.000
	2	0.389	0.678	0.671	0.395
MPPM(8)	1	0.000	0.000	0.000	0.000
	2	0.421	0.325	0.473	0.591

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

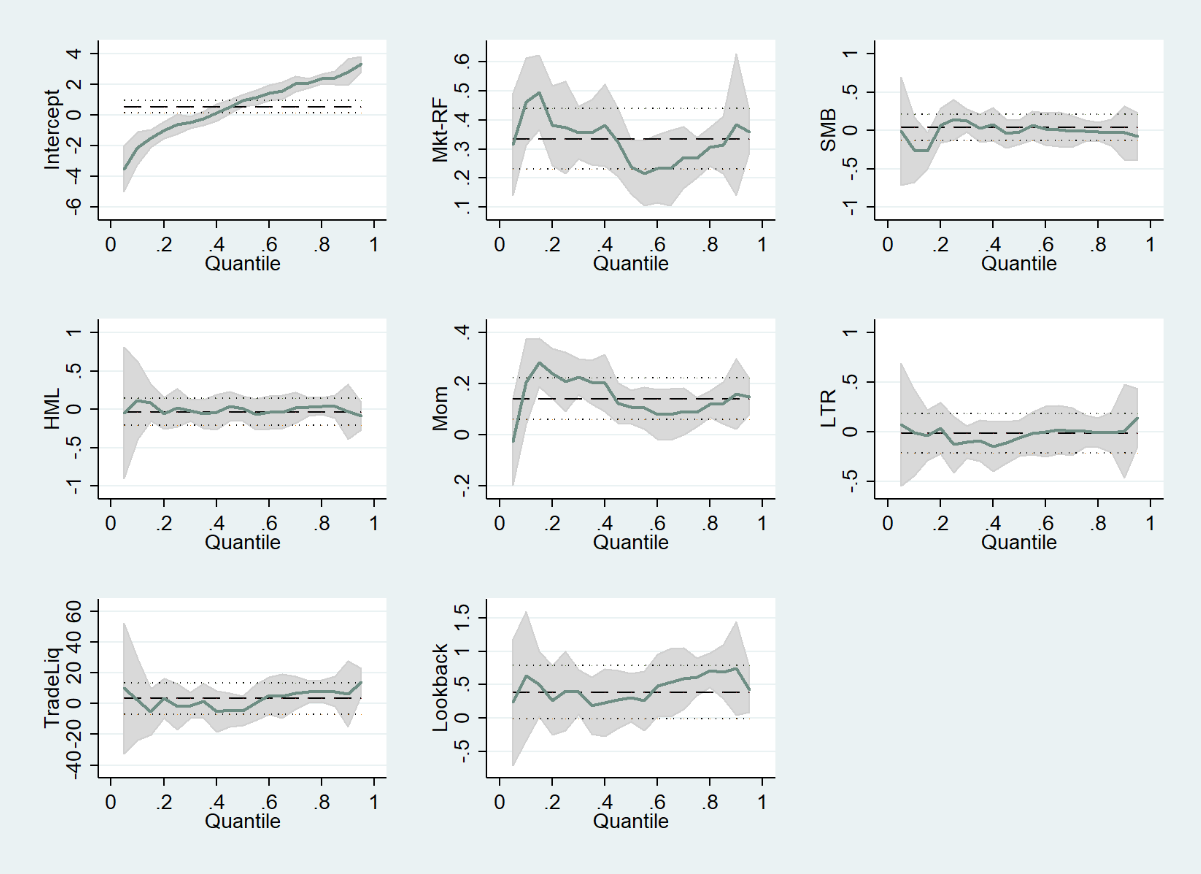

Figure 1. Marginal effects of risk factors on excess returns for top performing funds.
Each graph in the above figure depicts the relation between the size and the significance of the coefficient and the quantile of a given risk factor for top performing funds as measured by the manipulation proof performance measure with a risk aversion parameter of 3. The shaded areas 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*), liquidity (*TRADELIQ*) and lookback straddles return (*LOOKBACK*) factors.

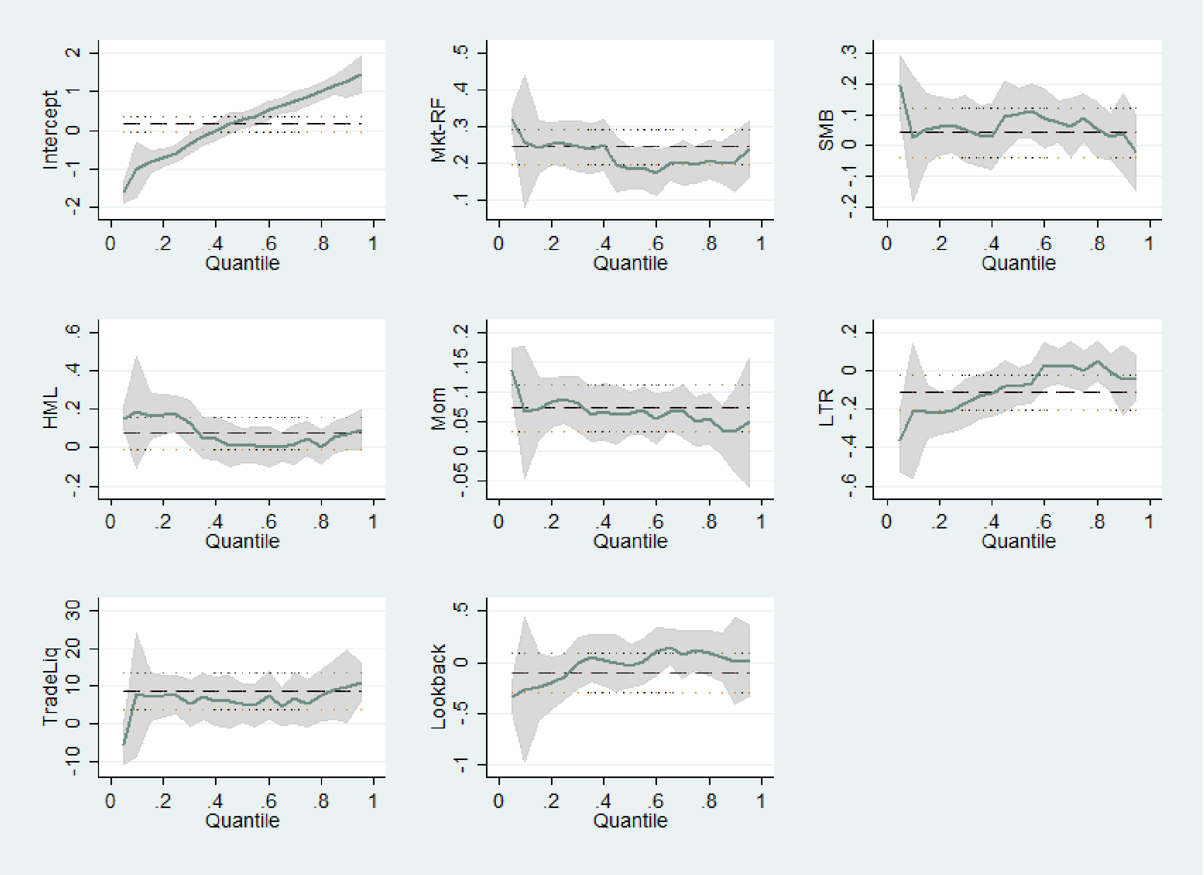

Figure 2. Marginal effects of risk factors on excess returns for mediocre performing funds. Each graph in the above figure depicts the relation between the size and the significance of the coefficient and the quantile of a given risk factor for mediocre performing funds as measured by the manipulation proof performance measure with a risk aversion parameter of 3. The shaded are 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*), liquidity (*TRADELIQ*) and lookback straddles return (*LOOKBACK*) factors.

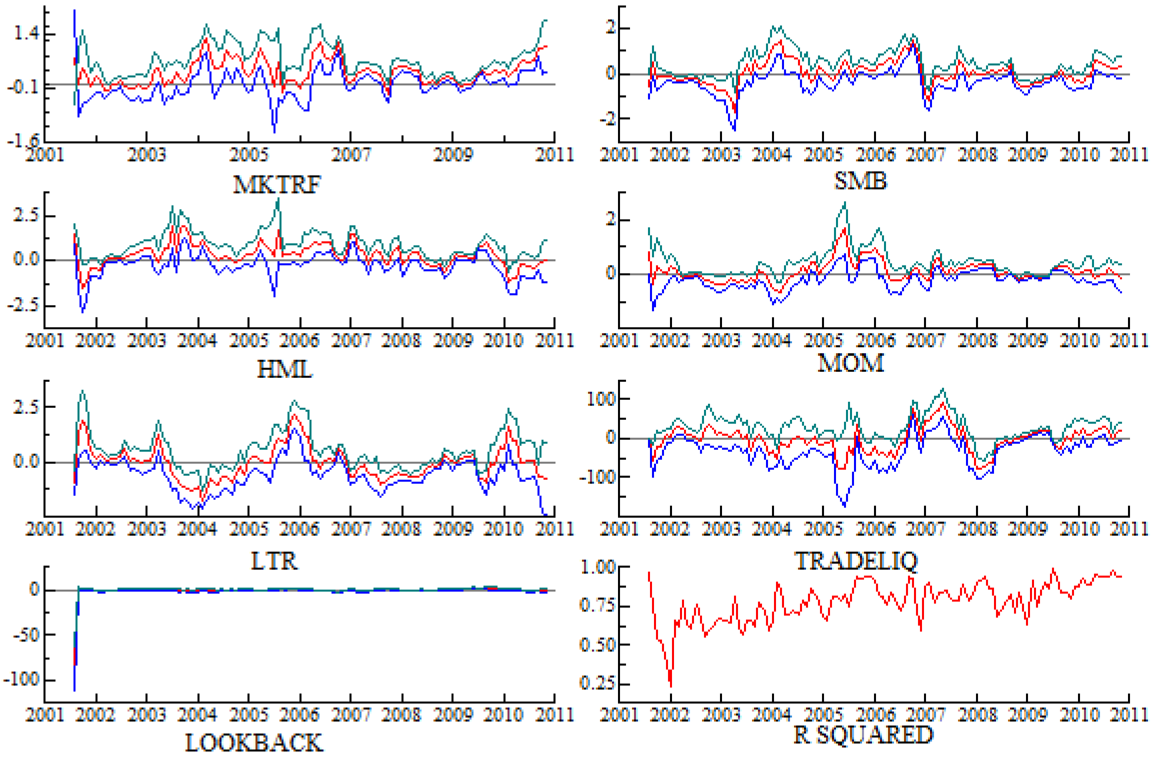

Figure 3. Time variation of the risk factors for top performing funds

Using a 12 month rolling window, these figures show the time varying estimated coefficients of the risk factors in Equation (7) and their upper and lower bounds 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 (*MKTRF*) and the size (*SMB*), growth (*HML*), momentum (*MOM*), momentum reversal (*LTR*), liquidity (*TRADELIQ*) and lookback straddles returns (*LOOKBACK*). The rolling time varying R^2 (*R SQUARED*) coefficients are also reported.

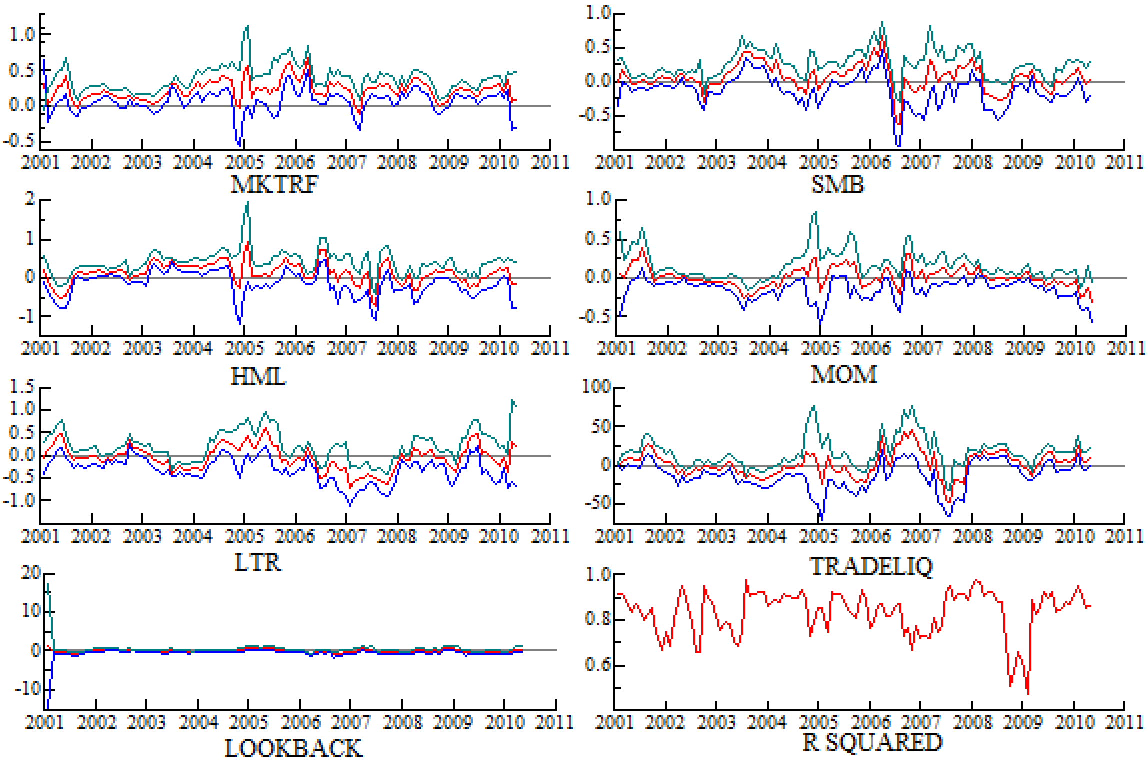

Figure 4. Time variation of the risk factors for mediocre performing funds

Using a 12 month rolling window, these figures show the time varying estimated coefficients of the risk factors in Equation (7) and their upper and lower bounds hat 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 (*MKTRF*) and the size (*SMB*), growth (*HML*), momentum (*MOM*), momentum reversal (*LTR*), liquidity (*TRADELIQ*) and lookback straddles returns (*LOOKBACK*). The rolling time varying R^2 (*R SQUARED*) coefficients are also reported.