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EDUARDO ALONSO MARZA DOS SANTOS

TAIL RISK IN THE HEDGE FUND INDUSTRY

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Dissertação apresentada à Escola de Economia de São Paulo da Fundação Getulio Vargas como requisito para obtenção do título de Mestre em Economia

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ABSTRACT

The dissertation goal is to quantify the tail risk premium embedded into hedge funds' returns. Tail risk is the probability of extreme large losses. Although it is a rare event, asset pricing theory suggests that investors demand compensation for holding assets sensitive to extreme market downturns. By definition, such events have a small likelihood to be represented in the sample, what poses a challenge to estimate the effects of tail risk by means of traditional approaches such as VaR. The results show that it is not sufficient to account for the tail risk stemming from equities markets. Active portfolio management employed by hedge funds demand a specific measure to estimate and control tail risk. Our proposed factor fills that void inasmuch it presents explanatory power both over the time series as well as the cross-section of funds' returns.
Keywords: Tail risk, Extreme value theory, Multifactor models, Hedge funds

RESUMO

O objetivo do trabalho é quantificar o prêmio de risco de cauda presente nos retornos de fundos de investimento americanos. Risco de cauda é o risco de perdas excepcionalmente elevadas. Apesar de ser um evento raro, a teoria de apreçamento de ativos sugere que os investidores exigem um prêmio de risco para reter ativos expostos a eventos negativos extremos (eventos de cauda). Por definição, observações extremas têm baixa probabilidade de estarem presentes na amostra, o que dificulta a estimação dos impactos de risco de cauda sobre os retornos e reduz o poder de técnicas tradicionais como VaR. Os resultados indicam que não é suficiente controlar somente para o risco de cauda do mercado de capitais. A gestão ativa de portfólio por parte dos gestores de fundos requer uma medida própria para estimação e o controle de risco de cauda. O fator de risco de cauda que propomos cumpre este papel ao apresentar poder explicativo tanto na série temporal dos retornos quanto no corte transversal.

Palavras-Chave: Risco de cauda, Valores extremos, Modelos multifatoriais, Fundos de investimento.

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1 Introduction

In the last years there have been profound changes in the way that money is managed. One indicator of these changes is the rapid growth of the hedge fund (HF) industry, whose assets on a global basis have gone from 39 billion at year-end 1990 to 1.93 trillion as of the second quarter of 2008. Figure 1 shows the recent pattern of hedge funds' assets under management. As we can see, the aggregate amount of resources controlled by hedge funds has decreased somewhat in the aftermath of the sub prime crisis, but has been catching up since. The more recent piece of data shows that the industry size is roughly 2.5 trillion dollars. Given its importance as major players in capital financial markets, as well as their particular risk-return profiles, hedge funds have been the object of extensive amount of research. Within said literature, since the crisis of 2007/08 interest has been built around extreme negative market conditions or tail risk.

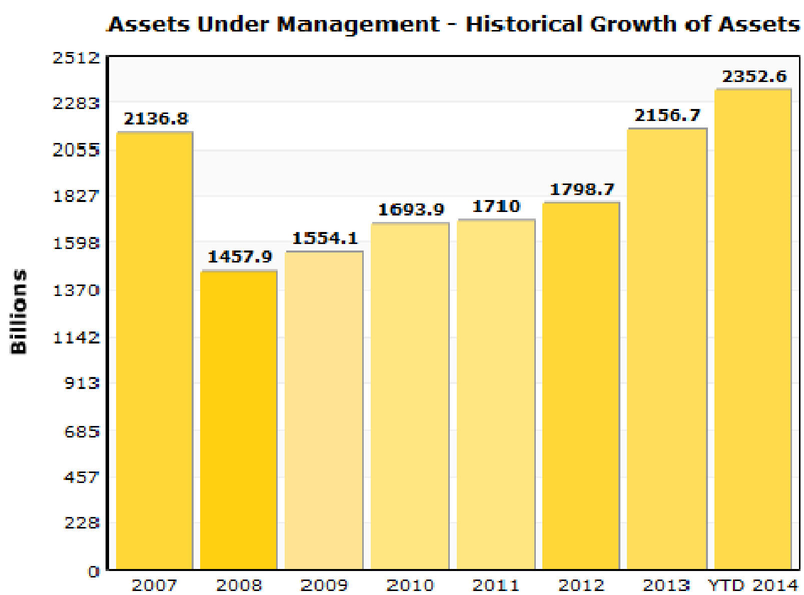

Figure 1 – Evolution of hedge funds AUM

Hedge fund active portfolio management makes assessing their risk profile pretty challenging. As Stulz (2007) points out, it is silly to assess the riskiness present in a hedge fund by means of return volatility only. One must also consider the higher order risks, such as tail risk. The author argues that the incentives of some hedge fund managers to produce the highest possible alpha may lead them to pursue tail risky investments. They may resort to the so-called "picking up nickels in front of a steamroller" strategies. These tend to produce a small positive gain most of the times, but also large losses every now and then. An example is the selling of deep out of the money options: most of the time the seller reaps a little premium but if prices suddenly spike (up for put options and down for calls) and the buyers exercise their options, the loss incurred could well surpass the accumulated profit from the selling. The effects of a tail event are more perverse the higher is the leverage ratio of a fund.

We believe that tail risk is an important determinant of the hedge fund performance and must therefore be accounted for. In spite of their rarity, tail events produce significant pricing implications for securities and, as we show in this dissertation, particularly to hedge funds. Their crowded trades and liberal use of leverage make the analysis of tail risk even more relevant, especially when one considers that hedge funds take positions in a plethora of different markets and countries. Their impact on global financial stability should not be underestimated. As Fung and Hsieh (1999)(pg. 19) emphatically put it:

> *Should one consider or plan for a "6 standard deviations" event? We do not believe this is the right question. Rather, it is more important to estimate the risk factors affecting a fund's returns and ask the question "How likely is the nightmare scenario that all factors hit their worst estimates at the same time". Bear in mind that it does not require "6 standard deviations" on all factors to generate a disaster.*

This dissertation introduces a new approach to estimate and control for tail risk. We add to previous literature by developing a tail risk factor especially fashioned

for the hedge fund world. We show that such factor has a great deal of explanatory power both over the cross-section and time-series dimensions, even when controlling for a panoply of different risk factors. In addition, we compare our factor with the one developed by Kelly and Jiang (2014) and show that the hedge fund tail risk (henceforth, HFTR) factor is superior. We confirm this result for both for the aggregate industry portfolio, as well as for each individual investment styles. Remarkably, HFTR performs better in all model specifications and is always selected by the regularization techniques we employ to estimate loadings in high dimensional models.

This dissertation is divided as follows. Section two revises the literature on tail risk and hedge fund performance analysis. We derive on the power law approach proposed by Kelly and Jiang (2014) in constructing our factor. The details of the methodology are presented in section three. Section four describes our dataset and the filters applied to it. Section five analyses the hedge fund loadings on tail risk both from an aggregated and style by style point of view. The fifth section identifies the major sources of risk affecting hedge funds performance, underscoring the predictive power of our HFTR factor also over the cross-sectional variational. The sixth section dig deeper on the determinants of tail risk loading, while the last presents concluding remarks. The appendix presents robustness checks and further details of our data.

2 Literature Review

This dissertation contributes to a strand of the asset pricing literature that analyze hedge fund's exposure to systematic risk factors. There has been a large number of papers addressing this issue. For instance, Asness, Krail and Liew (2001) present evidence that funds are not market neutral, carrying a significant amount of exposure to the market factor. Similarly, Patton (2009) finds evidence contrary to the market neutrality claims of some HF managers. Apart traditional measures of neutrality based on (partial) correlation, Patton proposes some new measures based on the returns distribution. These measures are: median neutrality, variance neutrality, value at risk neutrality and tail neutrality. He shows that there is significant positive dependence between hedge fund returns and some risk factors, even for the market-neutral style.

Fung and Hsieh (1997), Fung and Hsieh (2001), Fung and Hsieh (2004), Mitchell and Pulvino (2001) e Agarwal and Naik (2004) show that dynamic portfolio management as well as arbitrage strategies induce option-like pattern in HF returns. That is, instead of a linear relationship with the market return, the use of market timing results in a non linear association. The same goes to other assets benchmarks, such as currencies, commodities, etc. Thus, the authors argue, linear multi-factor models have a hard time trying to explain hedge funds' performance, particularly for those funds employing trend following strategies. Fung and Hsieh (2001) simulate the return of look-back straddle strategies for commodities, bonds and currencies to construct risk factors suited to assess the performance of trend following funds. The authors show that such factors possess a greater explanatory power relative to traditional assets indexes. The model is further extended in Fung and Hsieh (2004) to the seven factor benchmark which we employ our analysis.

Fung et al. (2008) use performance data from fund of funds to investigate risk in the HF industry during the period from 1995 to 2004. The evidence suggest that

returns are largely driven by exposure to the seven risk factors of Fung and Hsieh (2004) (henceforth, Fung and Hsieh 7 factor model). Indeed, upon controlling for these factors, the average fund produced no significant alpha during this period. However, there is a lot of variation across funds, with 22% of the hedge funds generating positive alpha. Relative to those with zero alpha, those funds have lower chances of being liquidated and receive greater net flows of capital.

Sadka (2010) provides evidence that HF returns are influence by equity liquidity. The author find that funds with significant exposure to liquidity risk have higher future returns than those funds with no such loading. In this paper we derive similar conclusions with our tail risk factor. Higher moment has taken also a great deal of attention. Agarwal, Bakshi and Huij (2009) examine funds' return exposure to volatility, asymmetry and kurtosis extracted from S&P 500 options as proxies for higher moment risks. They argue that strategies such as managed futures, event driven and long-short equity present significant exposure to such risks and suggest factors to control them.

More recently, a strand of the literature has tackled the issue of tail risk estimation by focusing on the cross-sectional information. Bollerslev and Todorov (2014) uses intra-daily data as well as data on options over the stocks in the S&P 500 and provide a framework for estimating the shape of the risk-neutral jump tails, and the time-variation therein, based on the cross-section of short maturity options, finding nontrivial temporal dependencies in both lower and upper tails. The left one thickens considerably during periods of market distress. This approach is obviously unfeasible in the hedge funds world, since high frequency data on performance is not available and we must resort to monthly data.

The tail risk phenomenon is intrinsically related to that of liquidity. This is so because hedge funds often invest in assets prone to liquidity crunches which implies they cannot unwind their positions without incurring big losses. Although we cannot partial out completely tail risk effects from liquidity ones, in this paper we employ the factor developed by Pastor and Stambaugh (2003) to control for market liquidity. They propose a monthly liquidity measure which is the average (across stocks) of the strength of volume return reversals. They argue that stock returns are affected

by innovations in aggregate liquidity, with more sensitive stocks carrying higher expected risk-adjusted returns. Any study of extreme financial events is largely dependent on the definition of tail risk used. Allen, Bali and Tang (2012) proposes an index of financial crash by employing quantiles of the cross sectional distribution of returns. The authors show that their index manages to forecast real economic depressions up to six months ahead. Our approach relates to theirs inasmuch we define tail events by means of quantiles, which implies that every month some funds will experience tail events, providing us with information about the aggregate level of tail risk in that month.

Following the general losses incurred during the sub prime crisis, investors were anxious to figure out how they could protect themselves from "black swan like" events that arise outside the usual three standard deviations band around the mean of return distribution. The 2014 unstable global market environment has undoubtedly revived both academics and practitioners interest in uncovering such protections. However, the most crucial step to hedging tail risk is to measure it. Technically, tail risk is defined as a higher-than-expected likelihood of an investment position moving more than two or three standard deviations away from the mid-range of the distribution of outcomes. Therefore, we choose to work with the methodology of Kelly and Jiang (2014) which develop an innovative measure of time-varying tail risk embedded in the cross-section of stock returns. Essentially, they assess the magnitude of individual stocks price declines every month to come up with a market-wide measure of common fluctuations in tail risk, exploiting the fact that every month some stocks are bound to experience tail events. Thus, instead of arbitrarily defining some extreme events in the time series of returns, the authors explore the richer cross-sectional information to extract the current level of tail thickness and, more importantly, model its dynamics. Moreover, they demonstrate how their measure is linked to traditional tail risk factors extracted from equity index options, and how it moves inversely with real economic conditions. The tail risk factor can be interpreted as they as an systematic crash risk state variable which must be accounted for when modeling fluctuations in agents' marginal utility.

Our approach in this dissertation is reminiscent of Kelly and Jiang (2012). In

an extension of their early work, the authors employ the tail risk measure extracted from equity data to explain the risk taking behavior of hedge funds. They document large, persistent exposures of hedge funds to crash risk and conclude that tail risk is an important determinant of the time series and cross-sectional variation of hedge funds returns. For instance, the same hedge funds that underperformed in the 1998 crisis presented lower returns during the 2008 crisis. Also, a one standard deviation positive shock to tail risk is associated with a contemporaneous decline of 2.88% per year in the aggregate hedge fund portfolio return. They conclude that a significant component of hedge fund returns can be regarded as compensation for providing "earthquake insurance", for example, by selling deep out of the money options.

3 Methodology

The estimation approach relies on a description of the lower tail of Hedge Funds' returns conditional distribution function. We do not postulate a specific parametric form for such distribution, but rather we employ the approach of Kelly and Jiang (2014) based on Extreme Value Theory to approximate the lower tail. Formally, conditional upon exceeding some threshold u_t and given information $\mathcal{F}_t$, the return $R_{i,t}$ of fund i at period t obeys the tail probability distribution

$$F_{u_t,i,t}(r) = P(\, R_{i,t} < r |\, R_{i,t} < u_t,\ \mathcal{F}_{t-1}) \sim \left(\frac{r}{u_t}\right)^{-\xi_{i,t}}, \tag{3.1}$$

where the relation $\sim$ describes tail equivalence at the lower support boundary of $R_{i,t+1}$, that is,

$$f \sim g \Leftrightarrow \lim_{u \to \infty} \frac{f(u)}{g(u)} = 1. \tag{3.2}$$

The focus of this dissertation is on the left tail of the return distribution, i.e. on extreme negative events. This is so because the marginal utility of agents is very high in bad states of the nature so that assets with higher payoff in such states are more valuable. We note that, even though the convention in extreme value theory is to represent a tail distribution as the right, or upper, tail. This is without loss of generality since returns in the negative tail are simply transformed to an upper tail representation via a sign change.

Our goal is to capture the dynamics of the tail exponent $\xi_{i,t}$. This parameter measures the thickness of distribution tails: the lower the parameter, the slower is the decay of the function towards zero as the argument approaches the boundary of the support. Hence, a small positive power law coefficient characterizes a thick lower tail. It is important to observe two aspects of this specification: (1) the semi parametric form above described regards the *conditional* probability measure, given

information available $\mathcal{F}_t$; (2) we are not interested in quantifying the tail thickness, but rather in estimating how it evolves over time.

In order to correctly identify tail risk, the $\xi_{i,t}$ parameters cannot vary freely between both the cross section and time dimensions. We thus follow Kelly and impose some restrictions over the parameters. He postulates a particular form to the exponent allowing fund specific fixed-effects and time effects. The key identification assumption is the multiplicative exponent of the power law

$$\xi_{i,t} = \frac{a_i}{\lambda_t}. \tag{3.3}$$

This hypothesis allows tail risk to change over time, without compromising identification. The idiosyncratic parameter a_i is assumed to be fixed over time and we rule out fund-time effects. To construct a risk factor, the quantity of interest is λ_t, given that it gauges the economy-wide tail risk. Although each fund has a different tail decay, as measured by the idiosyncratic parameter a_i, the relevant aspect for asset pricing purposes is the common dynamics of tail risk.

Theory predicts that economy-wide tail risk affects the stochastic discount factor and therefore justifies the inclusion of a tail factor in linear models. For instance, Berk, Green and Naik (1999) propose an exogenous discount factor with an economic motivation. Their results shed some light on how rare disaster risk is discounted under the risk neutral measure, relative to its expectation under the physical probability measure.

The conditional distribution function of the lower tail is then

$$F_{u_t,i,t}(r) = P(\,R_{i,t+1} < r|\,R_{i,t+1} < u_t,\ \mathcal{F}_t) = (\frac{r}{u_t})^{\frac{-a_i}{\lambda_t}}, \tag{3.4}$$

and the corresponding density function is

$$f_{u_t,i,t}(r) = \frac{a_i}{u_t\lambda_t}\left(\frac{r}{u_t}\right)^{-\frac{a_i}{\lambda_t}}. \tag{3.5}$$

It should be stressed that we do not make full parametric assumptions regarding the distribution of returns. The above power law model is valid only over the tail

domain of the distribution, which is the interval delimited by the tail threshold $(-\infty, u_t)$. Such formulation is motivated by the limit theorem of Balkema and Haan (1974) and Pickands (1975). Roughly, this result guarantees that for a large class of heavy tailed distributions for $R_{i,t}$ the conditional distribution function $P(R_{i,t+1} < r | R_{i,t+1} < u_t,\ \mathcal{F}_t)$ converges to a power law function when the limit u_t approaches the boundary of the support. As in Kelly and Jiang (2014), we use such approximation as an exact relation.

The tail threshold u_t determines the value at which the tail domain starts. Inappropriately small thresholds will contaminate the tail exponent estimates by using data from the bulk of the distribution, whose behavior can vary markedly from tail data. On the other hand, unduly extreme thresholds will result in noisy estimates resulting from too few observations. Although there are some methods for threshold selection, they usually require the estimation of additional parameters. The sampling error of this first step estimation may overcome the benefits of an data-driven threshold, and hence some authors advocate using a rule of thumb for u_t. In this dissertation, we follow Gabaix (2008) and pick the 5^{th} percentile as the tail threshold. According to Kelly and Jiang (2014), defining the tail domain by a quantile accommodates time-varying volatility.

The hypothesis of interest is that the stochastic discount factor is increasing in tail risk. In other terms, we wish to check if rare disasters carry a risk premium, even if they only occur rarely. Empirically, this implies that tail risk helps predict not only the time series of returns, but also the cross section of returns across the hedge fund industry. Given that investors are averse to extreme negative events, we expect that our factor exhibits a positive and significant price of risk, as well as helps explain the cross section variation in hedge funds' returns.

We employ Hill's (1975) maximum likelihood estimator to the cross section of monthly returns on every fund at month t. This classical estimator relies on a conditional maximum likelihood framework. Assume that the sample $R_1, R_2, \ldots, R_n$ comes from a unknown distribution function F such that

$$F(r) \sim cr^{-\rho}. \tag{3.6}$$

Assuming the relation above holds as an equality for $r > d$ where d is some threshold, inference on the exponential decay term ρ can be based on the conditional likelihood of $R_i \geq d$. Now, applying Renyi representation, we get

$$R_i = F^{-1}\left[\exp\left(-\left(\frac{e_1}{n} + \frac{e_2}{n-1} + \ldots + \frac{e_i}{n-i+1}\right)\right)\right], i = 1, \ldots, n \tag{3.7}$$

where e_i are standard i.i.d. exponential random variables. Assume we ordered the variables in decreasing order and let k be the largest j such that $R_j \geq d$. Then, conditional on $R_i \geq d$, we have that

$$e_i = (n-i+1)\left[\ln 1 - cR_{i-1}^{-\rho} - \ln 1 - cR_i^{-\rho}\right], i = 2, \ldots, n \; and \tag{3.8}$$

$$e_1 = -n \ln 1 - cR_1^{-\rho} \tag{3.9}$$

Given this, the conditional likelihood function of ρ is

$$L(\rho) = |J|\, exp\left[n \ln(1 - cR_1^{-\rho}) - \sum_{i=1}^{k} (n-i) \ln\left(\frac{1 - cR_i^{-\rho}}{1 - cR_{i-1}^{-\rho}}\right)\right] \tag{3.10}$$

In our context, the Hill estimator is given by

$$\lambda_t^H = \frac{1}{K_t} \sum_{k=1}^{K_t} \ln \frac{R_{k,t}}{u_t}, \tag{3.11}$$

where R_k, t is the k$^{\text{th}}$ return that exceeds the threshold u_t at month t; K_t is the total number of extreme returns at month t. Given our choice of tail threshold, K_t corresponds to 5% of the total number of funds with data available at month t. As will be shown in the next section, the number of reporting funds vary greatly during the period of analysis. The methodology, however, is robust to this peculiarity.

To obtain the Hill estimator, we use only the most extreme return observations. The non extreme observations are not informative of the current level of tail risk, but play a major role in the determination of the 5$^{\text{th}}$ percentile. Under the assumption

that every fund has the same *ex ante* probability of experiencing an extreme event, the expected value of the Hill estimator is perfectly correlated with the aggregate tail risk level λ_t

$$E_{t-1}\left[\frac{1}{K_t}\sum_{k=1}^{K_t} ln\frac{R_{k,t}}{u_t}\middle| \lambda_t, R_{k,t} < u_t\right] = \lambda_t\frac{1}{\bar{a}}. \tag{3.12}$$

where $\frac{1}{\bar{a}} = \frac{1}{n}\sum_{i=1}^{n}\frac{1}{a_i}$.

That is, the estimator is consistent to λ_t multiplied by the harmonic average of the idiosyncratic parameters a_i. If the probability of an extreme event is different between funds kelly shows that

$$E_{t-1}\left[\frac{1}{K_t}\sum_{k=1}^{K_t} ln\frac{R_{k,t}}{u_t}\middle| \lambda_t, R_{k,t} < u_t\right] = \lambda_t\sum_{i=1} n\frac{\omega_i}{a_i}, \tag{3.13}$$

where the weights are given by $\omega_i = \frac{p_i}{\sum_j p_j}$ and p_i is the probability that fund i realize an extreme negative return. In any case, the expected value of the estimator applied in a period-by-period fashion is equal to the parameter of interest λ_t at month t multiplied by a constant. Hence, the expected value of Hill's estimator is perfectly correlated with tail risk, and hence it suffices for any asset pricing test. Since we are interested in the time variation of the TR parameter we normalize the Hill estimate:

$$TR_t = \frac{\hat{\lambda_t}^H - \bar{\lambda}}{\sigma_\lambda}, \tag{3.14}$$

where the sample mean $\bar{\lambda}$ and the standard deviation σ_λ are defined as

$$\bar{\lambda} = \frac{1}{n}\sum_{t=1}^{T}\hat{\lambda_t^H}$$
$$\sigma_\lambda = \frac{1}{n}\sum_{t=1}^{T}\left(\hat{\lambda_t^H} - \bar{\lambda}\right).$$

4 Data

In this dissertation, we use data from Barclay Hedge's Academic Global Database. It contains information of 6,142 funds, either in operation or in the graveyard. The latter consists of those funds that no longer report to Barclay Hedge, including funds closed due to capital withdraw and those that no longer report returns and net flows to Barclay Hedge for internal reasons. Given that funds' performance information disclosure is absolutely voluntary, managers may strategically decide when to report performance. For instance, a young manager may want to wait a "good year" with high returns before registering her fund in a database. On the other hand, an old fund, with consolidated reputation, can reach such a point as to close itself for further capital and therefore has no longer the need for making its performance publicly available.

Barclay Hedge, formerly known as the Barclay Group, was founded in 1985, and consists of a team of research specialists, programmers, and data administration staff. The Barclay Hedge Alternative Investment Database tracks and analyses the performance of more than 6,000 hedge fund and managed futures investment programmes worldwide, including approximately 3,600 individual hedge funds and 1,200 funds of hedge funds. The Barclay Hedge classification is somewhat different from other sources of HF data. All the main strategies are represented, while sector funds are split. In addition, it is the only classification with a formal extra family of strategies that includes the less well represented ones, such as technical, fundamental and volatility trading amongst others. With this methodology, the most popular strategies remain cleaner. On the other hand, the fixed income classification remains too basic, with only one category for directional and non-directional strategies.

It should be stressed that both entry and exit of funds in the database are not random. This is a ubiquitous characteristic of hedge fund data, since full information disclosure is not mandatory in the USA. Birth and death of hedge funds and its

implications for performance analysis have not, to the best of our knowledge, drawn much attention by the literature and for that reason we choose to work with the graveyard of funds, avoiding potential biases that could arise otherwise. In addition, we employ commonly used filters in our dataset. Firstly, throughout this dissertation, performance is measured by monthly logarithmic returns net of all fees in excess of the risk free rate. Moreover, we consider only funds denominated in US dollars in our analysis and exclude fund-of-funds.

Hedge fund's (risk-unadjusted) performance datasets are subject to backfilling bias. It is common practice to backfill once a fund starts reporting performance to some database. Since this is so, a upwards bias might arise as managers wait 18 exceptionally good months before entering into the database. To prevent such distortion, we exclude the first 18 months of returns for every fund. The final sample contains 2,935 funds, whose performance data extends over the period from February of 1996 to December of 2010, comprising 179 monthly observations. Barclay Hedge classify funds into 88 categories, some of which have less than 3 distinct funds. However, we will conduct our style analysis only on those categories most representative of our universe of hedge funds. In particular, we demand that each category included presents at least 100 consecutive monthly returns, yielding 72 distinct categories (for more details, we refer to the appendix).

We proxy for the market return using the log returns on the S&P 500 index (source: Bloomberg). For the risk free rate, we use the three month Treasury Bill rate from the Federal Reserve Economic Data (FRED). The size and book-to-market factors of Fama and French (1993), as well as the momentum factor of Jegadeesh and Titman (2001), come from Kenneth French's website. The Fung et al. (2008) trend following factors are available at David Hsieh's personal website, whereas the remaining factors of Fung and Hsieh (2001), Fung and Hsieh (2004) come from Bloomberg. Finally, we thank Nikunj Kapadia and Chi Zhang for graciously sharing their data on the-risk neutral moment factors of Bakshi, Kapadia and Madan (2003). Finally, we thanks Bryan Kelly for gently sharing his Equity Tail Risk factor (henceforth, ETR).

5 Tail Risk In The Time Series

HFTR Loadings

The predictive power of the Equity Tail Risk over stock indexes was established in Kelly and Jiang (2014). However, as noted in Fung and Hsieh (1999), the use of dynamic trading strategies by hedge funds implies a non linear association between their performance and traditional asset classes. Thus, it is not clear if a measure of tail risk derived from information from stocks returns suffices to capture tail exposure of HF returns. This is why we propose a new measure of tail risk fashioned for the HF industry and derived directly from a panel of HF performance. Figure 2 contrasts the dynamics of both tail risk measures, both of which are standardized to have zero mean and standard deviation equal to one. As the figure shows, there are five HFTR spikes in our sample, which are not followed by corresponding movements in the ETR series. This suggests that our tail risk factor brings in new information about the extreme events risk hedge funds are exposed to on top of the information embedded in the equity industry.

To ground our view of tail risk as a systematic factor affecting hedge funds' returns, we rely on the convergence trading literature. As Stein (2009) shows, by pursuing the same strategies, guided by the same market signals, hedge funds inflict negative externalities on one another, namely overcrowding and over-leverage. The first stems from the fact that, for a broad class of quantitative trading strategies, a particular fund manager cannot know exactly how many others are using the same model and positioning in the same assets as her. In addition, the extensive use of leverage by hedge funds creates a situation in which idiosyncratic shocks become systematic ones, resulting in a industry-wide crash. To emphasize this last point, consider two managers that follow the same set of signals and buy the same stocks using leverage. If one of them is afflicted by a negative shock, which could stem from

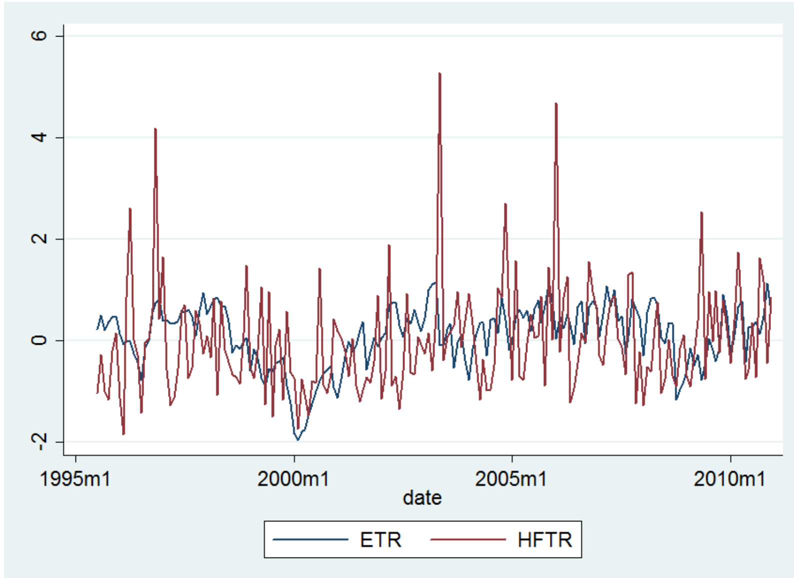

Figure 2 – Plot of equity tail risk (ETR) and hedge fund tail risk (HFTR).

a unrelated part of the portfolio, and be forced to liquidate some of the commonly held stocks to meet margin calls, this unwind movement can push prices down and inflict losses on the other fund. Forced to deleverage, the second fund generates another round of liquidations and prices declines potentially creating a fire-sale effect impacting a major share of the industry.

Khandani and Lo (2007) argue that overcrowding and over-leverage are major causes to the so called Quant Meltdown of 2007. During his crisis, which occurred in August of 2007, many popular quantitative strategies simultaneously experienced enormous negative returns, with daily movements absolutely atypical relative to historical volatility: daily losses of the order of 10 or more standard deviations were registered. Indeed, quantitative oriented managers did not correctly estimate the amount of money invested in the same strategies, neither the compounded effects on prices caused by over-leverage, which magnified the impact of its peers unwinding.

The analysis in this section aim to assess the predictive power of the HFTR factor over the time series of funds' excess returns, controlling for a performance model which includes the Fund and Hsieh seven factors. In order to do so, we form hedge fund portfolios and regress their performance on the HFTR factor together with the

other risk factors revealed by prior literature. For robustness, we also consider size-weighted portfolios in our analysis, using the volume of Assets Under Management of each fund as weights. Table 1 reports the descriptive statistics for the equal weighted portfolios. All styles but volatility trading present negative mean excess returns. The indexes volatility fall within the 1.5 - 3.5 band, with the exception of the technical and option strategies styles. Also, many styles have right skewed returns (except for the macro and tail risk ones) and present high kurtosis, in line with our premise of thick-tail distributions. It is remarkable how big of a loss some styles endure: options strategies experienced a 53.7% loss during or sample period, followed by emerging markets and its -44.5% spike. All styles show negative mean returns and roughly the same variance.

In order to assess the exposure to tail risk of the HF industry as a whole we construct an portfolio of all funds available in our sample. Barclay Hedge classifies funds into 88 categories, according to funds' self reporting. In this paper, we chose to aggregate these categories into 22 styles: CTA, balanced, closed end, convertible arbitrage, distressed securities, emerging markets, equity long only, equity long short, event driven, fixed income, fundamental, macro, market neutral, merger arbitrage, multi strategy, mutual fund, option strategies, sector, statistical arbitrage, tail risk, technical, volatility trading. The appendix documents the exact correspondence between styles and categories and describe each style.

Since the degree to which funds make use of leverage, short selling and derivatives is style dependent, we will repeat the analysis for every investment style in addition to the aggregate portfolio. The goal is to check whether or not tail risk exposure of funds is conditional on self-reported investment styles. As Fung and Hsieh (1999) point out, one cannot rely only on the investment style declared by the HF manager. Rather, an return-based approach, which relies on actual return data from performance records, can more reliably decompose the relevant sources of risk affecting returns. In the following analysis we focus our attention on those styles most representative in the sample, though we also estimate HFTR factor loadings for the remaining ones.

Next, we analyze the results of the regressions using equal-weighted portfolios. To take into account differences in funds' size, we repeat the analysis using size

weighted portfolios, constructed on the basis of funds' assets under management (AUM). Table 6 reports results for the portfolio of all funds available in our sample. For the full set of results, we refer to the appendix. A more thorough treatment of the relationship between the size of a HF and its tail risk exposure will be conducted in the 6^{th} section.

The Fung and Hsieh model has been extensively used as a benchmark for assessment of HF performance and manager skill. In this paper, we augment the model by including risk-neutral moment factors as in Bakshi, Kapadia and Madan (2003). The reason behind such extension is to check whether HFTR exposure is a spurious effect of kurtosis and/or skewness. The pricing implications of higher order moment were extensively studied by previous literature (e.g. Agarwal, Bakshi and Huij (2009)), whereas the research of tail risk pricing implications is much more recent.

We define the following variables: HFTR is the hedge fund tail risk factor whose construction was described in section 2; ΔTERM is the monthly change in the 10-year treasury constant maturity yield; ΔCREDIT is monthly change in the Moody's Baa yield less 10-year treasury constant maturity yield; SMB is the small minus big factor of Fama and French (1993); S&P 500 is the excess return on the Standard and Poors' index; PTFSCOM, PTFSFX and PTFSBD are the primitive trend following strategies respectively for commodities, currency and bonds; ΔRNSKEW, ΔRNKURT and ΔVIX are the variation in risk neutral skewness, kurtosis and variance, respectively. In addition, we include moving average terms to correct for autocorrelation in residuals when necessary.

Table 6 reports the regression estimates. In the first regression we control for the risk factors in the Fung and Hsieh's seven factor model, augmented by the high minus low book to market factor of Fama and French, the traded liquidity factor of Pastor and Stambaugh and the momentum factor of Jegadeesh and Titman. The market factor is not significant. This may be due both to market timing strategies or relative value ones, as pointed out by Fung and Hsieh (1999). The manager alternates the fund's net exposure to the market between long, short and neutral, which yields time-varying betas, according to the manager's view of the market. Hence, longer-term estimates of the systematic risk accruing from broad market movements might

be biased towards zero.

The loadings on the change in the long risk free yield (ΔTERM) and the credit spread (ΔCREDIT) are strongly negative. An increase of 1% in the credit spread factor, is associated with a return decrease of the aggregate HF index of 5.38%. Moreover, an increase of 1% in the credit term factor drops returns by 1.96 %, although this effect is diminished as we include more risk factors. As Fung and Hsieh (2002) points out, a negative loading on the credit spread variable indicates the presence of convergence trading strategies in fixed-income hedge funds. Some of those funds, which correspond to 353 funds in our sample, try to profit from mispricings of related bonds, going short on the overvalued security and long on the undervalued one. In essence, convergence trading is a bet on the convergence of the prices and therefore, it is exposed to a widen in yield spreads. When we augment our model with the higher moment proxies, the coefficient on ΔCREDIT decreases sharply (-3.29) but remains negative and highly significant.

On the other hand, trend following strategies in commodities and currency are also an important component of returns, as the coefficients of PTFSCOM and PTFSFX suggest. A one percent increase in the return of the Commodity trend following factor increases the return of the aggregate portfolio by 2.43%. A one percent increase in the return of PTFS Currency Lookback Straddle increases the return by 1.87%. Both coefficients are significant at the 5% level.

The HML coefficient is highly significant and negative (-0.13). However, its impact is severely reduced as we include more risk factors, keeping the statistical significance though. Interestingly, momentum is marginally significant for the equal weighted case, but its effect dies out when we further include the three risk neutral higher moment proxies ΔRNSKEW, ΔRNKURT and ΔVIX. The kurtosis and asymmetry factors are not significant, whereas the change in risk neutral volatility has a significant negative impact on returns. The last two columns show that including the HFTR factor increases the explanatory power of the model over the specification with ETR playing the role of tail risk factor. Indeed, the HFTR beta is much bigger in magnitude than the ETR beta, highlighting the superiority of our factor in controlling for tail risk.

In all, the evidence suggests that the HF industry as a whole has a significant exposure to tail risk, which is consistent with our previously stated hypothesis that some Hedge Fund managers tend to load on tail risky investments in pursuit of higher returns. This finding is robust to the inclusion of innovations in the three higher moment proxies: variance, skewness and kurtosis. The results for size weighted portfolios are qualitatively the same, with only marginal differences in the factor loadings estimates.

Style Analysis

Now we measure the impact of tail risk exposure for portfolios of different investment styles. In order to reasonably compare their risk profiles, we opt to aggregate the Barclay Hedge original categories into 22 investment styles and focus our attention on those with the largest number of funds. Table 2 reports the descriptive statistics of the risk factors. The three Fama-French factors show positive means, with the book to market factor (high minus low) exhibiting the grater variability. Momentum factor has the greater variability, while the primitive trend following factors exhibit relatively high kurtosis.

We begin with the Equity Long Only style. According to its description on Barclay's Hedge, EL managers use their stock picking skills to form optimal portfolios, usually relying on buy-and-hold strategies. As reported in the first column of table 7, the funds succeed in hedging overall market exposure, resulting on an insignificant coefficient of the market factor. Many funds employ momentum driven strategies, which result in a negative, significant at 1% level, exposure to the momentum risk factor of -0.23%. Including the higher moment proxies results in a highly significant negative exposure (-0.35) to the volatility factor, even though EL funds do not trade volatility directly. We would expect ETR to capture a good deal of the style exposure to tail risk, since funds of this style trade mostly equities. However, the EL style does not present significant equity tail risk exposure. In contrast, they do have a positive factor loading on HFTR, which is highly significant (at the 1% level). A

one standard deviation increase in HFTR is associated with an increase of 1.23% in Equity Long Only returns. Although their investment style is close to traditional index-tracking funds, the search for alpha to merit their higher remuneration might be driving EL funds to load on tail risk.

Table 8 presents the results for CTAs. In the first regression, the market factor is negative (-0.08) and significant only at the 10% level. This is likely due to omitted variables bias, since its significance improves in the models including the higher moment proxies. As we would expect, the trend following risk factor for commodities (PTFSCOM) is significant and highly positive in the basic model in the first column. However, its impact vanishes when we include the HFTR factor. The opposite is true for the bond trend following factor; controlling for the higher moment proxies, its effect is augmented both statistically (becoming significant at 1%) and economically, with a coefficient of 3.65. Volatility carries a loading of -0.13 in the second model, with its effect slightly reduced after controlling for HFTR, but remaining highly significant nonetheless. The fourth and fifth columns evidence that tail risk, as measured by our factor, is a important risk component in CTA returns, with a highly significant coefficient of 1.129.

The Emerging Markets results are reported in table 9. In the first model, the coefficient of the market factor and the HML are significant and negative, although small in magnitude. In contrast, the ΔCREDIT factor has a very large negative loading of -9.5. it is slightly reduced as we expand our model, but remains large relative to the other loadings. The opposite holds for the term factor, suggesting EM funds are more exposed to yield spread risk embedded in risky bonds and other securities issued in emerging countries.

Fixed income funds' results are presented in table 10. From the outset, we note that two moving average lags were included in all specifications two correct residuals. As expected, these funds do not possess significant risk exposure to the equity market, whereas both interest rate spreads factors are significant at the 1% level. The ΔCREDIT factor has a highly negative coefficient (-4.58) as does the ΔTERM factor (-1.6). For this style, only the bond trend following factor is significant.

Including the higher moment proxies does not change the results qualitatively,

but attenuates the magnitude of the estimates; the same pattern holds when we further include the ETR factor. In contrast, the HFTR is highly significant and positive, both as a substitute to ETR in the fourth model and together with it in the fifth, with coefficients of 0.24 and 0.26, respectively.

For the other styles, we estimate the more general model comprising both the Fama and French and Fung and Hsieh benchmarks, as well as the higher moment proxies together with the liquidity, moment and HFTR factors. Table 5 presents a summary of the corresponding alphas. All styles present positive alphas, with different magnitudes.

Figures 3 to 5 display the exposure to the HFTR factor of each style. In a nutshell, the results show that indeed HFTR is an important component of hedge fund returns for the majority of investment styles. Many styles have statistically significant and positive coefficients. For instance, the Fixed Income style has a small, although significant, exposure to HFTR, of about 0.25. Emerging Markets, CTA and Equity Long Only styles all have coefficients of roughly 1.4, all highly significant.

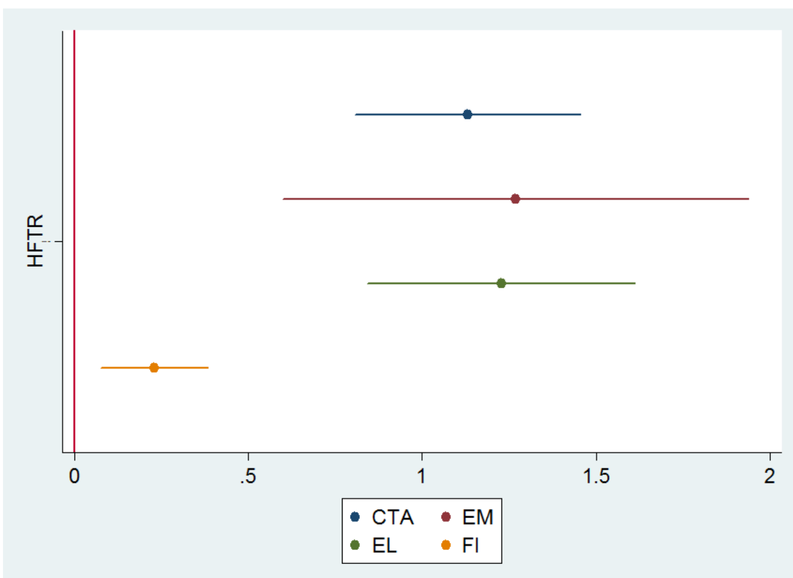

Figure 3 – HFTR betas by style

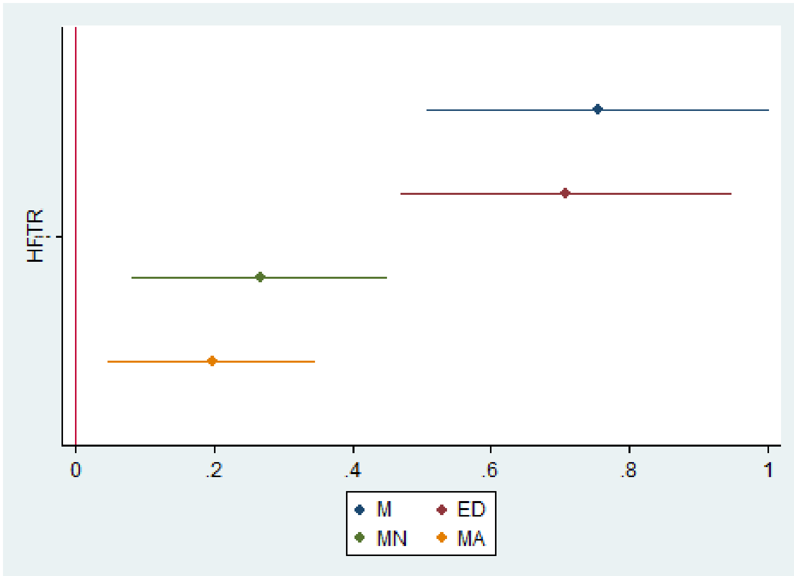

Figure 4 – HFTR betas by style

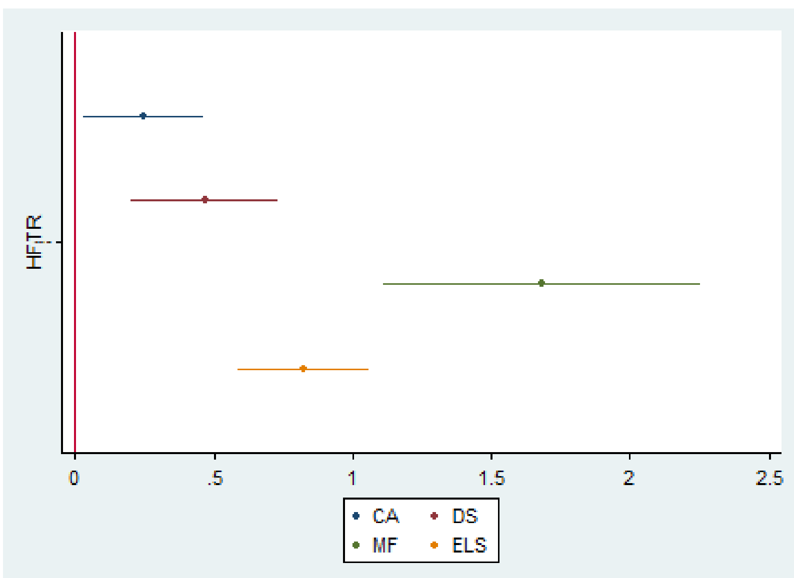

Figure 5 – HFTR betas by style

6 Factor Selection

Having established the higher predictive power of HFTR over ETR in the time series, we now turn our attention to the cross section. Specifically, this section investigates whether tail risk loadings helps explain the variation in style mean returns. Moreover, we take a closer look at the profile of each investment style, identifying their most significant loadings In order to make meaningful inferences over mean returns, we focus on those 72 categories which present at least 100 consecutive months of returns. The approach comprises two steps: in the first, tail risk loadings are estimated in a CAPM-like model, augmented by the tail risk factor. In order to compare which factor has more explanatory power, estimate loadings by using ETR in one specification and HFTR in another. In the second step, we regress mean style excess returns on these loadings (one observation per category, totaling 72 observations). Table 3 reports the results of the second step regressions. Although in theory both factors control for tail risk exposure, our results imply that ETR lags behind HFTR also in the cross-sectional dimension. The R-squared in the regression of average returns on HFTR-loadings, has a is 36%, while only 19% of historical performance variation across investment categories is explained by ETR-loadings. The evidence shows that, notwithstanding their rarity, tail risk explains a significant amount of the cross-sectional variation of average returns, indicating that extreme events are indeed priced in the hedge funds world.

Next we take a closer look at the different risk profiles induced by the diverse set of hedge funds' strategies. Since we do not know beforehand which is the correct model for performance assessment, in this section all risk factors are taken into account. We want to check whether our HFTR factor remains a significant source of risk even when we control for all the factors simultaneously in a single model. Doing so, however, renders unfeasible the estimation by OLS due to excessive number of regression coefficients. This is why, in this section, we employ a regularization technique to

simultaneously estimate and select the relevant risk factors in the regression. In particular, we use Tibshirani's (1996) least absolute shrinkage and selection operator (LASSO). This procedure prevents over-fitting by penalizing models with extreme parameter values - hence the term shrinkage. It does that by adding a ℓ_1 term to the minimization problem, weighted by a penalty parameter θ

$$\min_{\beta} \sum_{i=1}^{N} (y_i - \sum_{j=1}^{p} \beta_j x_{ij})^2 + \theta \sum_{j=1}^{p} |\beta_j| \,. \tag{6.1}$$

ABSTRACT

The dissertation goal is to quantify the tail risk premium embedded into hedge funds' returns. Tail risk is the probability of extreme large losses. Although it is a rare event, asset pricing theory suggests that investors demand compensation for holding assets sensitive to extreme market downturns. By definition, such events have a small likelihood to be represented in the sample, what poses a challenge to estimate the effects of tail risk by means of traditional approaches such as VaR. The results show that it is not sufficient to account for the tail risk stemming from equities markets. Active portfolio management employed by hedge funds demand a specific measure to estimate and control tail risk. Our proposed factor fills that void inasmuch it presents explanatory power both over the time series as well as the cross-section of funds' returns.
Keywords: Tail risk, Extreme value theory, Multifactor models, Hedge funds As shown by Zou (2006), the LASSO variable selection procedure is consistent. In the context of regularization, consistency translates into the capacity of the operator to recover the underlying model - which we implicit assume to be a subset of the explanatory variables at hand - as the sample size growths without bounds. In the statistical learning literature, it is common to define a set of desirable asymptotic characteristics a regularization procedure should have, the so called oracle properties, which are attained as long as the shrinkage parameter $\theta(n)$ converges to zero as the sample size n grows. Intuitively, if we allow the shrinkage parameter to grow at arbitrary large rates, the ℓ_1 penalty term would eventually dominate and collapse all betas to zero.

Notwithstanding the previous remarks, we will not use directly the LASSO estimates. As pointed out by Zou (2006) LASSO estimates are generally biased downward, and hence we choose to employ the Post-LASSO estimates as our estimates of factor loadings. These are simply OLS estimates on the model selected by the LASSO, that is, those factors with nonzero LASSO coefficient estimates. In this dissertation, we will follow Belloni, Chernozhukov and Hansen (2014) in our choice

of the shrinkage parameter

$$\theta = 2.2\sqrt{2n\ln(2\frac{p}{\ln n})} \tag{6.2}$$

where n is te number of observations and p is the number of parameters to be estimated. Multicollinearity amongst risk factors undermines precise selection of the most relevant risk factors for each style. Traditional estimation approaches are not suited to partial out marginal effects of independent variables over the dependent one when the former are strongly correlated. Table 4 reports the correlation matrix of the full set of factors. Some factors are strongly correlated, such as the changes in risk neutral skewness and kurtosis.

Figure 6 reports a summary of the LASSO and OLS estimates for factor loadings of the aggregate portfolio of all funds in our sample. The bars show, for each risk factor, the percentage of funds with significant loadings as estimated by both procedures: blue bars correspond to those OLS estimates which are significant at the 5% level whereas the red ones correspond to the non-zero Post-LASSO estimates. The results suggest that LASSO selection is generally more parsimonious than Least Squares. Indeed, in all risk factors, LASSO reports a smaller fraction of funds with non-zero exposure to that factor than ordinary least squares. For example, OLS estimates point towards a significant exposure to change in risk neutral skewness (ΔRNSKEW) for roughly 4% of the funds, while LASSO found none exposure whatsoever (no fund presented exposure to this factors)

Next, we investigate factor exposure of selected investment styles. Figure 7 shows OLS and Post-LASSO estimates for the CTA index. There are remarkable differences between the factor model chosen from least square methods and that of regularization methods. For instance, OLS finds roughly 2.5% of commodity trading advisors have exposure to kurtosis, while LASSO pushed the betas to zero. The same holds for the ΔTERM factor; on the other hand, both estimation procedures yielded very close results for ΔCREDIT (23% of CTAs have significant loadings). LASSO also found none exposure of CTAS to the ETR factor, what would be expected since tail events in the equity market do not translate automatically to corresponding events in commodities and/or FX markets.

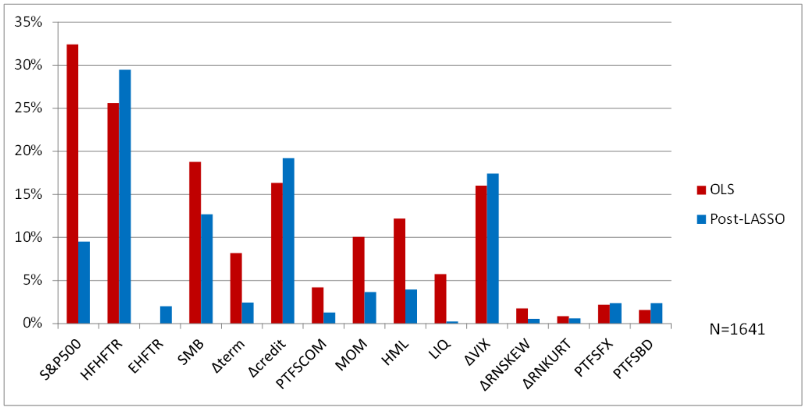

Figura 6 – Factor selection for all funds

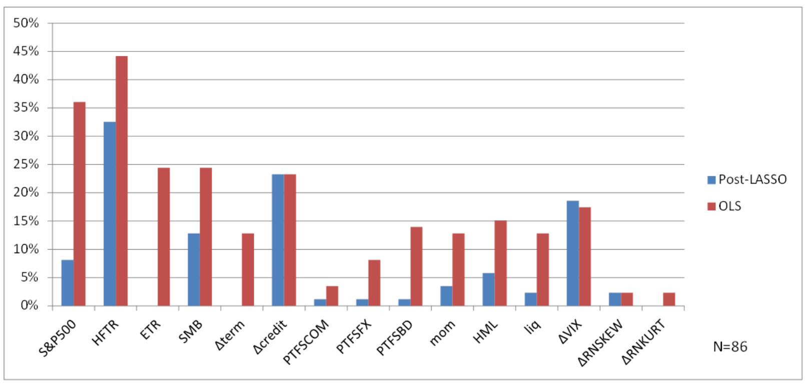

Figura 7 – Factor selection for CTAs

The results are similar to Emerging Markets style (figure 8). Roughly 45% of the funds have tail exposure as measured by HFTR and approximately 3% as measured by ETR. This result can be explained by the geographical orientation of such funds, which invest in more illiquid high-yield securities whose markets dry up suddenly even when equities markets are calm (i.e., are not withstanding tail events). Regarding the higher moment proxies, only volatility seems relevant, with 15% of funds presenting exposure to ΔVIX factor (LASSO estimates). The loadings for the Fung and Hsieh factors are not significant for the majority of funds, with the only exception being the credit spread factor, which is a major source of risk for about 20% of the EM funds.

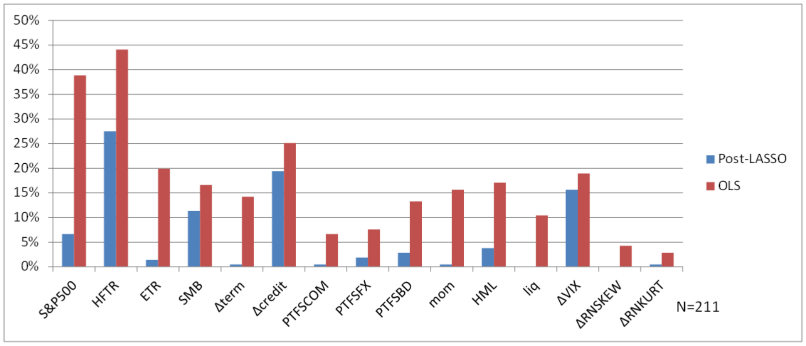

Figura 8 – Factor selection for EM style

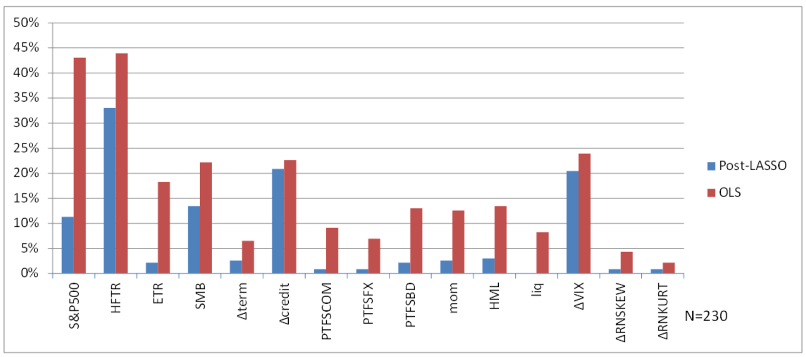

Figura 9 – Factor selection for EL style

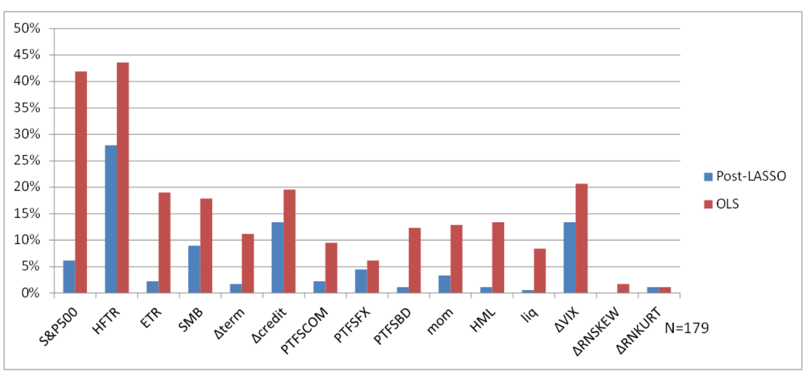

Figura 10 – Factor selection for FI style

7 Tail Risk and Hedge Funds' Characteristics

In this section we turn our attention to the relationship of tail exposure and the characteristics of individual funds. That is, we would like to answer the following question: do observable characteristics of HF help explain the variation in HFTR betas? Although we would like to explain the magnitude of tail exposure, doing so would require us to postulate a particular performance model general enough to capture the systematic risk exposure of each fund. To avoid such ad hoc hypothesis, we run time series LASSO regressions for each hedge fund i including all available risk factors and let the data tell us the relevant ones.

Figure 11 reports the histogram of the Post-LASSO tail factor loading estimates $\hat{\delta}_{i,TR}$. The percentage of funds with no tail risk exposure whatsoever is larger than 80%, whereas only two funds presents negative exposure. For this reason, we opt to work with an indicator variable that equals one if a particular fund has a positive tail risk exposure. Symbolically, we create an variable $HFTR_i$ which equals one if the estimated coefficient of $\hat{\delta}_{i,TR}$ is positive and zero otherwise.

The available set of characteristics includes fund age in months (AGE), fund size measured in millions of dollars (SIZE), return over the last 24 months (RET24), net fund flow over the last 24 months (FLOW24), as well as fund volatility (VOL), performance fees (PERFORMANCE), management fees (MANAGEMENT), a dummy indicating if the fund uses leverage (LEVERAGE), a dummy indicating if a High Water Mark provision is present (HWM), lock-up period (LOCKUP) and redemption periods (REDEMPTION). These last two variables are defined as the natural logarithm of one plus the number of days spanned by each period. To ease the interpretation, we standardize the monthly observations of each regressor by subtracting the cross-sectional mean and then dividing by cross-sectional standard deviation.

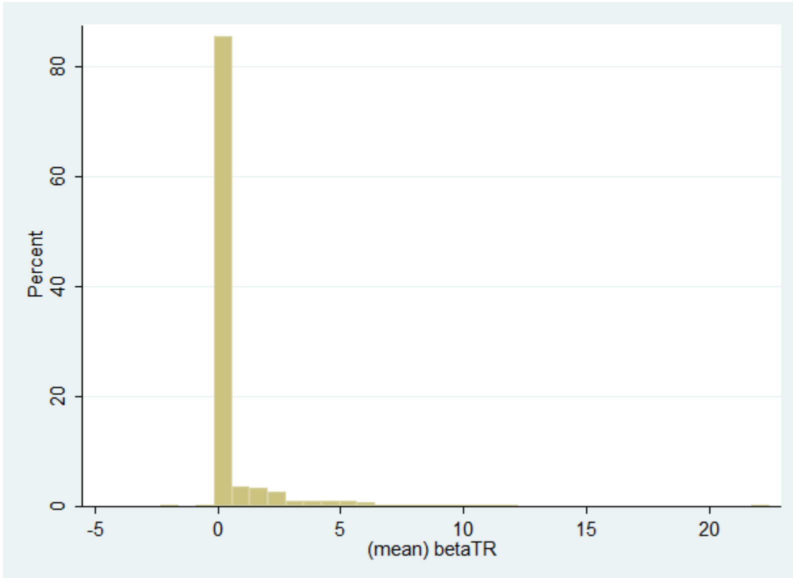

Figure 11 – Histogram of LASSO estimates of HFTR risk exposure

Denoting by y^* the latent variable, we postulate the following model

$$y^* = \backslash X_i' \backslash \beta + e_i \tag{7.1}$$

$$e_i \mid \backslash X_i \sim Normal\left(0, \sigma^2\right), \tag{7.2}$$

where the set of characteristics $\backslash X_i$ contains the variables $SIZE_i$, AGE_i, $RET24_i$, $FLOW24_i$, VOL_i, $REDEMPTION_i$, $LOCKUP_i$, $LEVERAGE_i$, HWM_i, $PERFORMANCE_i$ and $MANAGEMENT_i$.

Letting the cut-point be α and given the above model, the following conditional probabilities hold

$$P\left(HFTR_i = 0 \ \mid \backslash X\right) = \Phi\left(\alpha - \backslash X_i' \backslash \beta\right) \tag{7.3}$$

$$P\left(HFTR_i = 1 \ \mid \backslash X\right) = 1 - \Phi\left(\alpha - \backslash X_i' \backslash \beta\right) \tag{7.4}$$

We estimate the parameters of the model by maximum likelihood. Figure 12 shows the estimated probit beta coefficients for each characteristic in $\backslash X$.

In a nutshell, these results suggest that tail risk exposure is associated with funds' idiosyncratic characteristics. None of the dummies increases the likelihood of a HF

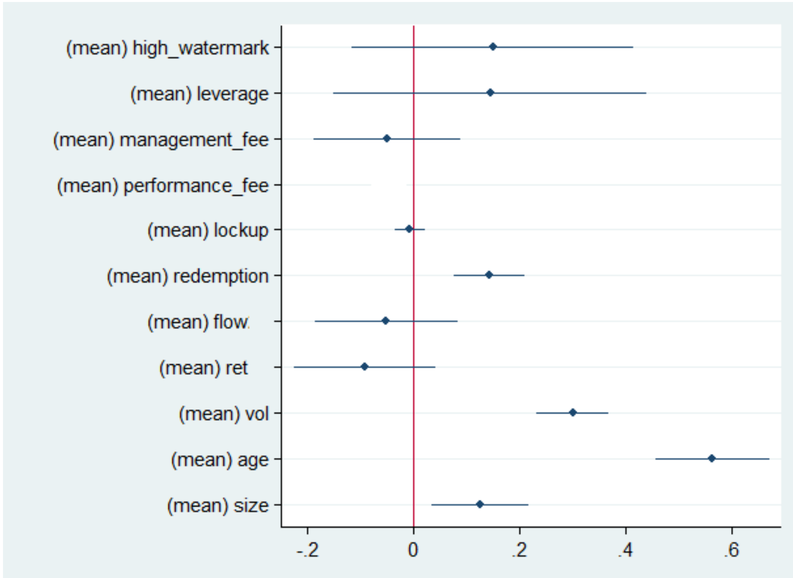

Figure 12 – Probit estimates

presenting positive HFTR beta. This suggests that constraints upon the managers' flexibility to work with leverage is not relevant HFTR-wise. It should be stressed that this result might be explained by omitted variables in the regressions. Specifically, our database does not possess indicators of the manager skin in the game, that is, whether or not the manager himself invests with the fund. The leverage dummy is not significant, indicating that funds' exposure to extreme events are not predicated on their ability to work with leveraged positions. The same holds for the high watermark dummy.

Performance incentives naturally condition the risk-taking behavior of hedge funds managers. One would expect that managers that capture a higher share of excess performance have stronger incentives to take riskier, more leveraged bets. If this is so, we would expect a positive coefficient of performance fee: higher fees are associated with higher probability of tail risk exposure. However, our results run on the opposite direction, since the performance fee regressor has a negative significant coefficient of -0.05, which means a higher performance fee actually decreases the probability of large tail risky bets by the manager. Of course, the same remarks about omitted variables applies here, but this result might be the explained by simultane-

ous bias as well. Being tail risk averse, investors might reward those managers that produce alpha without making use of risky leveraged bets that are highly profitable but result in huge losses every now and then. Indeed, given that tail risky strategies tend to produce relatively small gains over time, a small fee can induce managers to take riskier, more leveraged bets, which are capture by our HFTR factor. So, holding fixed other characteristics, a smaller exposure to tail events is rewarded with a higher performance fee as our results imply.

Most of tail risky assets are illiquid which implies that only funds not constrained to rapidly redeem its quotas when required can invest in such assets. For instance, these might include structured products, exotic derivatives or illiquid currencies. Such effects are not perfectly captured by the liquidity factor and hence we would expect that both the lock-up period and the redemption periods have positive coefficients: funds with longer lock-up and redemption periods have more flexibility to long illiquid assets. Such securities pose elevated risks to funds' cash flow management, since, in the event of a liquidity shock, their markets dry out, possibly rendering the manager unable to redeem its investors quotas. Longer redemption periods avoid this situation and therefore increases the probability of a positive tail risk exposure. Not surprisingly, controlling for redemption and lock-up period extinguishes the effects of mean net flows and mean returns upon tail risk loading.

8 Conclusion

The results on this dissertation corroborate the perception that tail risk is a ubiquitous attribute of the hedge fund industry business model. We have shown that hedge funds exhibit persistent exposures to extreme downside risk, making tail risk a key driver of hedge fund returns in both the time series and cross-section. A positive one standard deviation shock to tail risk is associated with a decline in the value of the aggregate hedge fund portfolio, while in the cross-section, investment styles that lose value during high tail risk episodes earn higher average monthly returns than funds that are tail risk hedged. We also find significant dispersion in the risk profile of the different styles, which contributes to factor analysis approach of classifying hedge funds.

We propose a new factor to control for extreme downside events risk, using information embedded in a panel of hedge funds performance. This approach can capture the effects of over-crowding and over-leverage on producing tail events in hedge funds' performance on top of the risk stemming from the equities market. We compare the explanatory power of our measure with that firstly derived by Kelly and Jiang (2014) and find that our factor has greater predictive power. Upon controlling for tail risk derived from the panel of returns, the loadings on ETR vanish both for the aggregate portfolio of hedge funds and for each investment style. When confronted with the other risk factors, HFTR presents significant positive loadings for a remarkable share of funds of all investment styles. Tail risky bets can be explained by hedge funds characteristics, in particular by their size, age and performance incentives. For future research, it would be interesting to explicit model hedge funds birth and death and its relationship with our tail risk factor.

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APPENDIX A – Data Sources

As a robustness check, we report in table 12 the results for the size (AUM) weighted portfolio. Although showing marginal differences in magnitude, the results found are qualitatively the same as the equal weighted case. Unreported results sustain this observation for size portfolios of each investment style analyzed in this paper.

- For more information regarding the descriptions of each category, we refer to the homepage:
  http://www.barclayhedge.com
- The Fama French factors and the momentum factor are available at Kenneth French website:
  http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/index.html
- The Fung and Hsieh factors are available at David Hisieh homepage:
  http://people.duke.edu/ dah7

Appendix B – Tables

Table 1 – Descriptive statistics for equal weighted indexes

Style	mean	sd	skewness	kurtosis	min	p25	p50	p75	max
CTA	-1.959	3.238	-0.789	4.454	-16.625	-4.215	-1.504	0.499	5.172
balanced	-1.158	3.258	-0.304	3.658	-10.840	-3.274	-0.603	0.907	9.242
convertible arbitrage	-1.840	2.972	-0.373	4.026	-12.185	-3.763	-1.674	0.162	6.392
distressed securities	-1.764	3.243	-0.469	4.938	-15.331	-3.714	-2.026	0.246	7.605
emerging markets	-1.916	6.397	-1.976	12.559	-44.526	-5.346	-0.684	1.816	12.572
equity long only	-1.785	4.279	-0.452	4.056	-19.209	-4.437	-1.731	1.290	9.627
equity long short	-1.905	2.697	-0.023	2.642	-9.711	-3.837	-1.954	0.149	4.689
event driven	-1.827	2.986	-0.568	4.829	-15.079	-3.694	-1.981	0.264	6.281
fixed income	-1.867	2.689	-0.424	3.739	-11.939	-3.674	-2.264	0.497	4.612
fundamental	-1.997	3.011	-0.364	2.576	-9.723	-4.341	-1.602	0.149	4.247
macro	-1.911	2.654	0.0528	2.497	-7.475	-4.017	-1.742	0.074	6.155
market neutral	-2.167	2.375	-0.463	3.092	-10.895	-4.011	-2.131	0.0214	4.291
merger arbitrage	-2.021	2.123	-0.554	4.826	-12.895	-3.725	-1.993	-0.217	3.135
multi strategy	-1.765	2.296	-0.517	4.487	-11.681	-3.162	-1.967	-0.016	4.073
mutual fund	-1.874	5.280	-0.172	4.246	-18.349	-5.168	-1.168	1.490	18.756
option strategies	-1.738	6.130	-3.795	30.723	-53.696	-3.035	-0.463	1.135	20.417
sector	-1.898	3.748	-1.228	8.038	-23.969	-4.286	-1.378	0.682	6.414
statistical arbitrage	-0.837	3.318	-0.7692	3.764	-11.305	-1.966	-0.212	1.166	7.198
tail risk	-2.730	3.958	0.451	4.121	-10.421	-4.813	-2.265	-1.256	6.559
technical	-1.927	4.128	-0.040	2.885	-12.734	-4.371	-2.060	0.855	10.187
volatility trading	0.964	1.766	-0.758	4.214	-3.559	-0.040	1.330	2.056	4.027

Notes: We report descriptive statistics for equal weigthed indexes (percentage) returns for each hedge-fund style. The sample period ranges from February of 1996 to December of 2010, comprising 179 monthly observations. The statistics p25 and p75 represent the 25^{th} and 75^{th} percentiles, respectively.

Table 2 – Descriptive statistics for the risk factors

Factors	mean	sd	skewness	kurtosis	min	p25	max
ΔS&P 500	0.004	0.048	-0.822	4.153	-0.186	-0.021	0.092
SMB	0.001	0.036	0.072	6.590	-0.162	-0.025	0.172
HML	0.210	4.538	-0.128	7.925	-20.790	-1.700	19.720
MOM	0.441	5.993	-1.453	10.827	-34.720	-1.540	18.390
LIQ	0.009	0.042	0.603	5.617	-0.101	-0.013	0.210
CREDIT	0.005	0.240	1.297	12.439	-0.790	-0.100	1.530
TERM	-0.013	0.282	0.048	4.047	-1.080	-0.220	0.950
PTFSBD	-0.019	0.146	1.378	6.127	-0.260	-0.131	0.689
PTFSFX	0.007	0.186	1.108	4.368	-0.300	-0.122	0.692
PTFSCOM	0.003	0.138	1.230	5.436	-0.230	-0.085	0.648
ΔVIX	0.029	4.616	0.152	4.117	-15.280	-2.450	20.500
ΔRNSKEW	0.000	0.517	0.035	3.217	-1.505	-0.303	1.285
ΔRNKURT	0.009	4.395	0.152	4.117	-11.595	-2.593	15.585
ETR	0.090	0.982	-0.837	3.638	-1.952	-0.271	1.148
HFTR	0.024	1.003	1.681	8.087	-1.848	-0.718	5.288

Notes: We report descriptive statistics for the set of risk factors. The period ranges from February of 1996 to December of 2010, comprising 179 monthly observations.

Table 3 – Tail risk and the cross-section of style returns

Loadings	$\bar{R}$	$\bar{R}$	$\bar{R}$
ETR		0.270***	-0.002
		(0.068)	(0.095)
HFTR	0.320***		0.338***
	(0.052)		(0.079)
Constant	-1.611***	-1.182***	-1.627***
	(0.100)	(0.078)	(0.120)
Categories	72	72	72
R-squared	0.36	0.19	0.38

Notes: This table reports the results of regression of style mean returns ($\bar{R}$) on their corresponding tail risk loadings. The first column uses our HFTR factor. The second one uses Kelly's ETR risk measure, while the third column confronts the two factors. There are 72 styles, whose loadings where calculated in fist-step time series regressions of excess returns on the market excess return and the corresponding tail risk factor. Standard errors in parenthesis.

Table 4 – Correlation matrix of risk factors

Factors	ΔS&P 500	SMB	HML	MOM	LIQ	CREDIT	TERM	PTFSCOM	PTFSFX	PTFSBD	ΔVIX	ΔRNSKEW	ΔRNKURT	ETR	HFTR
ΔS&P 500	1.00														
SMB	0.07	1.00													
HML	-0.08	0.14	1.00												
MOM	-0.02	-0.16	-0.70	1.00											
LIQ	-0.08	0.08	-0.06	0.02	1.00										
CREDIT	-0.08	-0.12	-0.14	0.32	-0.27	1.00									
TERM	-0.03	0.04	0.07	-0.20	0.17	-0.54	1.00								
PTFSCOM	-0.07	-0.13	-0.12	0.23	-0.10	0.22	-0.12	1.00							
PTFSFX	-0.15	-0.15	-0.06	0.14	-0.17	0.35	-0.19	0.35	1.00						
PTFSBD	0.01	0.08	-0.06	0.00	-0.03	0.22	-0.28	0.19	0.26	1.00					
ΔVIX	-0.13	-0.17	-0.02	0.24	-0.15	0.49	-0.15	0.12	0.22	0.20	1.00				
ΔRNSKEW	0.07	0.01	-0.05	0.06	0.04	-0.03	-0.01	0.04	-0.06	0.07	0.14	1.00			
ΔRNKURT	-0.03	0.00	0.03	-0.07	-0.03	-0.01	0.07	0.02	0.07	-0.06	-0.25	-0.91	1.00		
ETR	0.05	-0.01	0.00	0.03	0.14	-0.11	0.07	0.03	-0.02	-0.15	-0.06	-0.01	0.01	1.00	
HFTR	-0.02	0.13	0.06	-0.10	0.06	-0.22	0.05	0.22	0.13	-0.05	-0.25	-0.12	0.18	0.22	1.00

Notes: This table presents the correlations among the full set of risk factors.

Table 5 – Summary of alphas for the general model

Style	alpha	se	months
CTA	0.697***	0.162	179
balanced	0.618**	0.219	96
convertible arbitrage	0.629***	0.109	179
distressed securities	0.892***	0.134	179
emerging markets	1.015**	0.336	179
equity long only	0.965***	0.193	179
equity long short	0.852***	0.119	179
event driven	0.766***	0.119	179
fixed income	0.679***	0.0771	179
fundamental	0.560***	0.138	179
macro	0.675***	0.124	179
market neutral	0.386***	0.0924	179
merger arbitrage	0.601***	0.0752	179
multi strategy	0.852***	0.0894	179
mutual fund	1.096***	0.284	179
option strategies	0.926**	0.341	179
sector	0.903***	0.171	179
statistical arbitrage	0.587*	0.271	72
technical	0.782***	0.223	179

This table presents the estimates of alphas for each style. Equal weigthed portfolios of each style are formed and their exposures are estimated for the general model. This model includes HFTR, TERM, CREDIT, SMB, S&P 500, PTFSCOM, PTFSFX, PTFSBD, ΔRNSKEW, ΔRNKURT and ΔVIX. Standard errors in parenthesis. We omit those styles with a insufficient number of return observations

Table 6 – Tail risk exposure in the hedge fund industry

Factors	(1)	(2)	(3)	(4)	(5)	(6)
ΔS&P 500	-0.307	-5.452*	-5.347*	-3.485	-2.924	
	(2.620)	(2.786)	(2.803)	(2.157)	(2.196)	
SMB	7.303*	1.024	1.092	-2.067	-1.842	
	(3.951)	(3.478)	(3.513)	(2.764)	(2.824)	
CREDIT	-5.380***	-3.292***	-3.321***	-2.374***	-2.438***	
	(0.666)	(0.824)	(0.825)	(0.696)	(0.657)	
TERM	-1.958***	-1.595**	-1.595**	-1.286**	-1.243**	
	(0.565)	(0.626)	(0.631)	(0.632)	(0.624)	
PTFSBD	-1.603	-0.178	-0.220	-0.00269	-0.126	
	(0.985)	(1.105)	(1.109)	(1.013)	(0.998)	
PTFSFX	1.871**	1.289*	1.295*	0.512	0.518	
	(0.892)	(0.701)	(0.704)	(0.593)	(0.601)	
PTFSCOM	2.427**	2.457**	2.470**	0.613	0.562	
	(1.119)	(1.040)	(1.032)	(0.919)	(0.897)	
HML	-0.132***	-0.103**	-0.102**	-0.102***	-0.0984***	
	(0.0414)	(0.0433)	(0.0442)	(0.0348)	(0.0356)	
LIQ	0.922	2.890	2.978	1.121	1.291	
	(2.888)	(2.935)	(2.932)	(2.658)	(2.691)	
MOM	-0.0650*	-0.0289	-0.0284	-0.0237	-0.0208	
	(0.0347)	(0.0345)	(0.0348)	(0.0290)	(0.0292)	
ΔVIX		-0.189***	-0.189***	-0.156***	-0.156***	-0.187***
		(0.0325)	(0.0327)	(0.0269)	(0.0276)	(0.0194)
ΔRNSKEW		0.185	0.179	-0.121	-0.154	
		(0.605)	(0.607)	(0.546)	(0.542)	
ΔRNKURT		0.0323	0.0318	-0.0228	-0.0275	
		(0.0743)	(0.0745)	(0.0730)	(0.0728)	
MA(1)		0.281***	0.277***	0.302***	0.263***	0.202***
		(0.0758)	(0.0762)	(0.0747)	(0.0793)	(0.0588)
ETR			-0.0923		-0.348*	
			(0.264)		(0.200)	
HFTR				0.960***	0.993***	1.040***
				(0.110)	(0.109)	(0.0987)
Alpha	1.060***	1.077***	1.083***	1.076***	1.099***	1.047***
	(0.142)	(0.168)	(0.168)	(0.144)	(0.139)	(0.135)
Months	179	179	179	179	179	179

This table presents the results of time series regressions of a equal weighted portfolio of all funds in the sample. Standard errors in parentheses. Last column presents Post LASSO estimation results. *** pvalue<0.01, ** pvalue<0.05, * pvalue<0.1

Table 7 – Tail risk exposure for equity long only funds

Factors	(1)	(2)	(3)	(4)	(5)	(6)
ΔS&P 500	0.00510	-0.110***	-0.109***	-0.0770**	-0.0715**	
	(0.0418)	(0.0374)	(0.0376)	(0.0327)	(0.0330)	
SMB	7.269	-9.342**	-9.308*	-12.23***	-11.91***	
	(6.110)	(4.714)	(4.937)	(4.157)	(4.398)	
CREDIT	-8.252***	-4.647***	-4.715***	-3.789***	-3.886***	-3.607***
	(1.148)	(1.193)	(1.177)	(1.099)	(1.052)	(0.988)
TERM	-1.611*	-1.196	-1.210	-0.888	-0.870	
	(0.963)	(0.869)	(0.862)	(0.843)	(0.819)	
PTFSBD	-4.814***	-1.442	-1.520	-1.479	-1.652	
	(1.518)	(1.550)	(1.547)	(1.532)	(1.503)	
PTFSFX	1.217	0.279	0.247	-0.527	-0.593	
	(1.767)	(1.162)	(1.157)	(1.072)	(1.064)	
PTFSCOM	0.529	0.00253	0.0352	-2.123	-2.119	
	(2.565)	(1.947)	(1.937)	(1.878)	(1.908)	
HML	-0.398***	-0.305***	-0.304***	-0.302***	-0.301***	
	(0.0693)	(0.0614)	(0.0616)	(0.0549)	(0.0544)	
LIQ	0.908	3.530	3.954	0.422	0.981	
	(4.381)	(4.100)	(4.130)	(3.833)	(3.919)	
MOM	-0.231***	-0.139**	-0.137**	-0.135***	-0.133***	
	(0.0622)	(0.0546)	(0.0546)	(0.0507)	(0.0507)	
ΔVIX		-0.349***	-0.351***	-0.307***	-0.310***	-0.371***
		(0.0465)	(0.0464)	(0.0433)	(0.0435)	(0.0396)
ΔRNSKEW		-0.290	-0.294	-0.735	-0.768	
		(0.891)	(0.881)	(0.831)	(0.823)	
ΔRNKURT		0.0179	0.0175	-0.0496	-0.0535	
		(0.105)	(0.105)	(0.101)	(0.101)	
MA(1)		0.402***	0.404***	0.405***	0.392***	0.219***
		(0.0751)	(0.0754)	(0.0790)	(0.0816)	(0.0719)
ETR			-0.296		-0.544	
			(0.407)		(0.355)	
HFTR				1.134***	1.168***	1.045***
				(0.215)	(0.215)	(0.232)
Alpha	1.199***	1.252***	1.273***	1.252***	1.289***	1.119***
	(0.255)	(0.283)	(0.293)	(0.263)	(0.266)	(0.255)
Months	179	179	179	179	179	179

This table presents the results of time series regressions of equal weighted portfolios of equity long only (EL) funds. Standard errors in parentheses. Last column presents Post LASSO estimation results *** pvalue<0.01, ** pvalue<0.05, * pvalue<0.1

Table 8 – Tail risk exposure for commodity trading advisors

Factors	(1)	(2)	(3)	(4)	(5)	(6)
ΔS&P 500	-0.0768*	-0.0865**	-0.0882**	-0.0801**	-0.0774**	
	(0.0407)	(0.0391)	(0.0393)	(0.0332)	(0.0351)	
SMB	8.856	6.660	6.656	1.722	1.661	
	(5.615)	(5.398)	(5.510)	(4.359)	(4.429)	
CREDIT	-1.876	-0.665	-0.627	0.794	0.767	
	(1.200)	(1.175)	(1.200)	(1.009)	(1.055)	
TERM	-2.385***	-2.047**	-2.044**	-1.541*	-1.538*	
	(0.782)	(0.822)	(0.821)	(0.841)	(0.854)	
PTFSBD	2.812*	3.652***	3.759***	4.481***	4.388***	5.226***
	(1.436)	(1.336)	(1.371)	(1.189)	(1.201)	(1.173)
PTFSFX	1.724	1.624	1.595	0.411	0.433	
	(1.152)	(1.079)	(1.117)	(0.971)	(0.998)	
PTFSCOM	3.554***	3.138**	3.086**	0.851	0.835	
	(1.331)	(1.306)	(1.313)	(1.216)	(1.217)	
HML	-0.00503	0.0348	0.0337	0.0382	0.0423	
	(0.0532)	(0.0556)	(0.0561)	(0.0438)	(0.0465)	
LIQ	1.042	0.420	0.0627	-0.470	-0.132	
	(4.984)	(4.668)	(4.651)	(4.299)	(4.375)	
MOM	0.00620	0.0417	0.0405	0.0550	0.0582*	
	(0.0424)	(0.0429)	(0.0426)	(0.0344)	(0.0350)	
ΔVIX		-0.132***	-0.132***	-0.107***	-0.105***	
		(0.0438)	(0.0441)	(0.0373)	(0.0379)	
ΔRNSKEW		0.502	0.508	0.276	0.272	
		(0.850)	(0.875)	(0.802)	(0.817)	
ΔRNKURT		0.0904	0.0909	0.0307	0.0294	
		(0.119)	(0.120)	(0.112)	(0.112)	
ETR			0.168		-0.190	
			(0.306)		(0.255)	
HFTR				1.129***	1.154***	1.221***
				(0.171)	(0.169)	(0.150)
MA(1)					-0.0132	-0.0107
					(0.0788)	(0.0745)
Alpha	0.945***	0.952***	0.943***	0.957***	0.966***	0.993***
	(0.204)	(0.206)	(0.205)	(0.184)	(0.186)	(0.172)
Months	179	179	179	179	179	179

This table presents the results of time series regressions of equal weighted portfolios of Commodity Trading Advisor (CTA) funds. Standard errors in parentheses. Last column presents Post LASSO estimation results. *** pvalue<0.01, ** pvalue<0.05, * pvalue<0.1

Table 9 – Tail risk exposure for emerging markets funds

Factors	(1)	(2)	(3)	(4)	(5)	(6)
ΔS&P 500	-0.200***	-0.180**	-0.180**	-0.143**	-0.141*	
	(0.0718)	(0.0712)	(0.0785)	(0.0679)	(0.0737)	
SMB	15.18	6.513	6.526	3.692	3.864	
	(10.54)	(9.857)	(9.935)	(9.802)	(9.824)	
CREDIT	-9.513***	-6.213***	-6.219***	-5.421**	-5.475**	-8.888***
	(1.917)	(2.163)	(2.162)	(2.211)	(2.195)	(1.551)
TERM	-2.972*	-2.456	-2.457	-2.197	-2.178	
	(1.798)	(1.837)	(1.837)	(1.803)	(1.781)	
PTFSBD	-7.004***	-3.822*	-3.826*	-3.929*	-4.007*	
	(1.909)	(2.264)	(2.325)	(2.197)	(2.244)	
PTFSFX	-0.0279	-0.870	-0.870	-1.738	-1.733	
	(1.981)	(1.814)	(1.819)	(1.799)	(1.806)	
PTFSCOM	-0.375	-1.563	-1.562	-3.690	-3.703	
	(3.032)	(2.657)	(2.671)	(2.598)	(2.618)	
HML	-0.377***	-0.225**	-0.225**	-0.220**	-0.220**	
	(0.109)	(0.0969)	(0.0972)	(0.0935)	(0.0938)	
LIQ	10.70	11.44	11.45	8.044	8.161	
	(9.103)	(8.714)	(9.117)	(8.631)	(8.998)	
MOM	-0.189**	-0.0808	-0.0806	-0.0768	-0.0764	
	(0.0942)	(0.0849)	(0.0861)	(0.0836)	(0.0840)	
ΔVIX		-0.387***	-0.387***	-0.342***	-0.344***	
		(0.0856)	(0.0871)	(0.0833)	(0.0840)	
ΔRNSKEW		1.088	1.088	0.604	0.586	
		(1.393)	(1.393)	(1.457)	(1.458)	
ΔRNKURT		0.174	0.174	0.105	0.103	
		(0.164)	(0.164)	(0.183)	(0.184)	
MA(1)	0.376***	0.446***	0.445***	0.454***	0.448***	0.251***
	(0.0824)	(0.0722)	(0.0729)	(0.0715)	(0.0721)	(0.0826)
ETR			-0.0173		-0.244	
			(0.751)		(0.728)	
HFTR				1.170***	1.183***	1.482***
				(0.324)	(0.333)	(0.347)
Alpha	1.265**	1.246***	1.247**	1.245***	1.263***	1.258***
	(0.496)	(0.481)	(0.487)	(0.476)	(0.473)	(0.461)
Months	179	179	179	179	179	179

This table presents the results of time series regressions of equal weighted portfolios of Emerging Markets (EM) funds. Standard errors in parentheses. Last column presents Post LASSO estimation results. *** pvalue<0.01, ** pvalue<0.05, * pvalue<0.1

Table 10 – Tail risk exposure for fixed income funds

Factors	(1)	(2)	(3)	(4)	(5)	(6)
ΔS&P 500	-0.00273	-0.00481	-0.00397	0.000776	0.00234	
	(0.0139)	(0.0142)	(0.0141)	(0.0140)	(0.0138)	
SMB	-0.406	-0.675	-0.577	-1.480	-1.407	
	(1.936)	(1.962)	(1.982)	(1.885)	(1.930)	
CREDIT	-4.577***	-4.441***	-4.516***	-4.254***	-4.330***	-4.011***
	(0.338)	(0.406)	(0.391)	(0.413)	(0.391)	(0.248)
TERM	-1.600***	-1.561***	-1.559***	-1.472***	-1.460***	
	(0.287)	(0.319)	(0.328)	(0.320)	(0.321)	
PTFSBD	-1.452***	-1.432**	-1.493***	-1.413***	-1.498***	
	(0.506)	(0.558)	(0.557)	(0.534)	(0.529)	
PTFSFX	-0.109	-0.0556	-0.0443	-0.218	-0.216	
	(0.479)	(0.488)	(0.493)	(0.476)	(0.475)	
PTFSCOM	0.193	0.144	0.161	-0.417	-0.428	
	(0.670)	(0.694)	(0.684)	(0.685)	(0.679)	
HML	-0.0236	-0.0213	-0.0202	-0.0218	-0.0201	
	(0.0287)	(0.0307)	(0.0307)	(0.0283)	(0.0280)	
LIQ	1.133	1.032	1.291	0.599	0.901	
	(1.518)	(1.490)	(1.536)	(1.434)	(1.463)	
MOM	-0.0339	-0.0334	-0.0316	-0.0327	-0.0303	
	(0.0215)	(0.0236)	(0.0245)	(0.0214)	(0.0218)	
ΔVIX		-0.0110	-0.0129	-0.00329	-0.00489	
		(0.0155)	(0.0157)	(0.0151)	(0.0151)	
ΔRNSKEW		0.115	0.108	0.105	0.0934	
		(0.416)	(0.405)	(0.394)	(0.384)	
ΔRNKURT		-0.00720	-0.00740	-0.0177	-0.0186	
		(0.0471)	(0.0466)	(0.0464)	(0.0457)	
MA(1)	0.328***	0.333***	0.331***	0.300***	0.288***	0.255***
	(0.0676)	(0.0659)	(0.0645)	(0.0683)	(0.0675)	(0.0538)
MA(2)	0.287***	0.307***	0.303***	0.322***	0.308***	
	(0.0772)	(0.0804)	(0.0842)	(0.0770)	(0.0797)	
ETR			-0.256		-0.296*	
			(0.184)		(0.166)	
HFTR				0.241***	0.255***	0.191**
				(0.0905)	(0.0851)	(0.0960)
Alpha	0.954***	0.956***	0.974***	0.956***	0.977***	0.983***
	(0.123)	(0.130)	(0.132)	(0.125)	(0.127)	(0.102)
Months	179	179	179	179	179	179

This table presents the results of time series regressions of equal weighted portfolios of Fixed Income (FI) funds. Standard errors in parentheses. Last column presents Post LASSO estimation results. *** pvalue<0.01, ** pvalue<0.05, * pvalue<0.1

Table 11 – Tail risk exposure for macro funds

Factors	(1)	(2)	(3)	(4)	(5)	(6)
ΔS&P 500	0.0124	0.00628	0.00851	0.00872	0.0126	
	(0.0319)	(0.0313)	(0.0315)	(0.0270)	(0.0271)	
SMB	1.404	0.0232	0.0281	-4.022	-4.018	
	(3.640)	(3.509)	(3.687)	(2.787)	(2.926)	
CREDIT	-2.903***	-2.164**	-2.215**	-1.292	-1.329	
	(0.734)	(0.913)	(0.925)	(0.826)	(0.816)	
TERM	-2.453***	-2.265***	-2.269***	-2.097***	-2.062***	
	(0.661)	(0.699)	(0.700)	(0.694)	(0.666)	
PTFSBD	-1.463	-0.919	-1.063	-0.736	-0.884	
	(1.134)	(1.172)	(1.168)	(1.018)	(0.977)	
PTFSFX	2.197**	2.108**	2.147**	1.196	1.200	
	(0.860)	(0.865)	(0.860)	(0.824)	(0.806)	
PTFSCOM	2.288*	2.002	2.072	0.703	0.697	
	(1.219)	(1.291)	(1.278)	(1.206)	(1.202)	
HML	-0.0695*	-0.0440	-0.0425	-0.0528	-0.0490	
	(0.0392)	(0.0397)	(0.0396)	(0.0380)	(0.0359)	
LIQ	3.310	2.932	3.409	2.677	3.324	
	(3.829)	(3.774)	(3.768)	(3.205)	(3.186)	
MOM	-0.0222	0.000910	0.00241	0.00660	0.0100	
	(0.0324)	(0.0322)	(0.0327)	(0.0298)	(0.0295)	
ΔVIX		-0.0813**	-0.0810**	-0.0577	-0.0584	
		(0.0412)	(0.0412)	(0.0379)	(0.0372)	
ΔRNSKEW		0.383	0.375	0.318	0.278	
		(0.790)	(0.781)	(0.668)	(0.658)	
ΔRNKURT		0.0751	0.0745	0.0490	0.0436	
		(0.0843)	(0.0837)	(0.0750)	(0.0743)	
ETR			-0.224		-0.449**	
			(0.222)		(0.219)	
HFTR				0.761***	0.803***	0.902***
				(0.135)	(0.132)	(0.114)
MA(1)				0.183**	0.158**	0.102
				(0.0812)	(0.0770)	(0.0778)
Alpha	0.928***	0.932***	0.943***	0.929***	0.957***	0.982***
	(0.144)	(0.140)	(0.138)	(0.153)	(0.146)	(0.152)
Months	179	179	179	179	179	179

This table presents the results of time series regressions of equal weighted portfolios of Macro (M) funds. Standard errors in parentheses. Last column presents Post LASSO estimation results. *** pvalue<0.01, ** pvalue<0.05, * pvalue<0.1

Table 12 – Tail risk exposure for size weighted industry portfolio

Factors	(1)	(3)	(6)	(9)	(12)
ΔS&P 500	-0.373	-2.466	-2.509	-1.057	-0.692
	(2.574)	(2.571)	(2.572)	(1.900)	(1.968)
SMB	6.179	3.507	3.488	0.0388	0.101
	(3.906)	(3.653)	(3.645)	(2.694)	(2.731)
CREDIT	-3.420***	-2.346***	-2.334***	-1.288**	-1.336**
	(0.650)	(0.778)	(0.775)	(0.636)	(0.637)
TERM	-2.109***	-1.884***	-1.884***	-1.489***	-1.468***
	(0.504)	(0.563)	(0.565)	(0.527)	(0.538)
PTFSBD	0.187	0.749	0.771	1.214	1.131
	(1.162)	(1.053)	(1.066)	(0.852)	(0.838)
PTFSFX	1.775**	1.571**	1.566**	0.700	0.708
	(0.728)	(0.675)	(0.675)	(0.573)	(0.577)
PTFSCOM	2.372**	2.417**	2.409**	0.466	0.399
	(1.052)	(1.035)	(1.039)	(0.889)	(0.873)
HML	-0.0953**	-0.0773*	-0.0776*	-0.0741**	-0.0711**
	(0.0418)	(0.0413)	(0.0417)	(0.0315)	(0.0320)
LIQ	0.992	1.612	1.548	0.234	0.536
	(3.109)	(2.845)	(2.842)	(2.421)	(2.474)
MOM	-0.00375	0.0104	0.0100	0.0203	0.0243
	(0.0354)	(0.0355)	(0.0354)	(0.0268)	(0.0271)
ΔVIX		-0.0935***	-0.0935***	-0.0658**	-0.0647**
		(0.0316)	(0.0316)	(0.0261)	(0.0266)
ΔRNSKEW		0.460	0.463	0.213	0.194
		(0.658)	(0.663)	(0.611)	(0.611)
ΔRNKURT		0.0511	0.0513	-0.00266	-0.00566
		(0.0786)	(0.0791)	(0.0760)	(0.0754)
MA(1)		0.141*	0.142*	0.118	0.0862
		(0.0837)	(0.0837)	(0.0776)	(0.0790)
ETR			0.0429		-0.250
			(0.220)		(0.156)
HFTR				0.950***	0.980***
				(0.101)	(0.0977)
Alpha	0.855***	0.862***	0.860***	0.864***	0.878***
	(0.128)	(0.137)	(0.137)	(0.109)	(0.106)
Months	179	179	179	179	179

This table presents the results of time series regressions of a size (AUM) weighted portfolio of all funds in the sample. Standard errors in parentheses. Last column presents Post LASSO estimation results. *** pvalue<0.01, ** pvalue<0.05, * pvalue<0.1