Tail risk exposures of hedge funds: Evidence from unique Brazilian data

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Abstract: This paper examines tail risk in the Brazilian hedge fund industry. We rely on a unique data set of daily returns for every hedge fund in Brazil, dead or alive. By employing the universe of hedge funds, we ensure the absence of selection, survivorship, and instant history biases. We estimate tail risk measures based on the cross-section of both equity and hedge-fund returns. In particular, we rely on the expected shortfall of the cross-section distribution both under the physical and risk-neutral measures. We find that tail risk estimates are very different not only across asset classes (equity vs hedge fund), but also across probability measures (physical vs risk neutral). We also show that, although hedge funds in Brazil seem to exhibit more contemporaneous exposure to equity tail risk, which also partially explains the cross-section of their expected returns, hedge fund tail risk entails higher predictive ability to performance over time.

JEL classification numbers: G11, G20

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1 Introduction

Hedge funds exhibit some very significant exposures to systematic risks despite the recurrent claim of market neutrality (Asness, Krail, and Liew, 2001; Patton, 2009; Bali, Brown, and Caglayan, 2011; Distaso, Fernandes, and Zikes, 2013). Among others, Fung and Hsieh (1997, 2001, 2004), Mitchell (2001), Agarwal and Naik (2004), and Fung, Hsieh, Naik, and Ramadorai (2008) claim that hedge fund returns have a nonlinear relation with market return due to their dynamic trading strategies. Although Agarwal, Bakshi, and Huij (2009) show that hedge funds display significant exposure to higher-moment risks, it turns out that only market volatility (and not skewness and kurtosis) explains the cross-sectional variation in hedge fund returns (Bali, Brown, and Caglayan, 2012). In a similar line, Agarwal, Arisoy, and Naik (2017) find that uncertainty about equity market volatility helps predict hedge fund returns both in the cross-section and over time. Sadka (2010) find that hedge funds also load on liquidity risk, whereas Buraschi, Kosowski, and Trojani (2014) document that it is also important to control for correlation risk when analyzing hedge fund performance. Finally, Jiang and Kelly (2012) report that hedge funds entail substantial exposure to equity tail risk (ETR).

However, there is a channel through which hedge funds may cause systematic risk by themselves. Stulz (2007) claims that some of their trading strategies resemble selling earthquake insurance in that they win small prizes in normal times, but suffer heavy losses if a tail event occurs. A sufficiently high initial loss may trigger fire sales that could well affect the entire financial industry. To appreciate why, recall that hedge funds typically follow very similar strategies and market signals (Stein, 2009), especially those that delve into high frequency trading (HFT). As arbitrageurs are uncertain about how many other traders have similar positions, coordination problems arise, pushing prices further away from their fundamentals. Leverage intensifies these damaging effects of overcrowding, so that an initial idiosyncratic shock may end up becoming a systematic shock to the entire market.[1] Fire sales may then spread the shock to the industry by inflicting losses in funds with similar positions, causing new rounds of fire sales from leveraged funds. Kondor's (2009) convergence trading equilibrium model illustrates well this mechanism.

Almeida, Fernandes, Santos, and Valente (2016) attempt to gauge the tail risk that stems from

[1] See Richardson, Saffi, and Sigurdsson (2017) for more details on deleveraging risk.

convergence trading in the hedge fund industry using the power law methodology by Kelly and Jiang (2014). They show that hedge funds in the US have more exposure to the tail risk in their own industry than to the tail risk coming from equity markets. Additionally, their hedge fund tail risk (HFTR) indicator helps not only predict future returns, but also explain the cross-sectional difference in hedge fund returns. Agarwal, Ruenzi, and Weigert (2017) obtain similar findings for equity-oriented hedge funds by relying on the lower tail dependence of hedge fund returns and market returns, scaled by the ratio of their respective expected shortfalls.

In this paper, we assess the importance of HFTR relative to ETR in the Brazilian fund industry. The motivation is simple. HFT activity is very recent in Brazil, with most traders setting shop only as from 2010. In particular, HFT activity at the Brazilian Stock Exchange (B3) has been increasing steadily from 0.6% in December 2010 to 14% of the total volume in December 2014 (CVM, 2014). Just for the sake of comparison, ESMA (2014) estimates that HFT activity accounted for 43% of the volume traded and 76% of the number of orders in the EU equity markets by May 2010, whereas SEC (2014) notes that HFT typically responds for more than 50% of total volume in any US-listed stock since 2010. If the channel for exposure to hedge fund tail risk indeed hinges on high frequency trading, then we should find a relatively higher exposure to equity tail risk rather than to hedge fund tail risk in Brazil.

A second reason to employ Brazilian data is the unique set of information to which we have access. Differently from the US, every investment fund in Brazil must report returns (and other relevant information) to the regulatory agency (CVM) on a daily basis (Domingues, 2012). The ANBIMA database we use contains the universe of investment funds in Brazil, dead or alive, avoiding selection, survivorship, and instant history biases (Fung and Hsieh, 2004). In addition, it also provides information on their trading strategy based not only on self-classification but also on style analysis. This allows us to consider only investment funds that trade on multiple markets, including derivatives and illiquid assets, so as to restrict attention to hedge funds. In particular, our data set includes daily returns on over 6,800 Brazilian hedge funds from June 2002 to June 2015. The fact that we observe returns at the daily frequency is convenient because it allows us to estimate monthly equity and hedge-fund tail risks (ETR and HFTR, respectively) based on the expected shortfalls under the physical distribution as in Agarwal, Ruenzi, and Weigert (2017) and under the risk-neutral measure as in Almeida, Ardison, Garcia, and Vicente (2017).

The literature on the estimation of tail risk under the risk-neutral measure is growing fast. Bollerslev and Todorov (2011) use intraday futures data and the cross-section of S&P 500 options to estimate an investors' fear index. They show that compensation for tail risk accounts for a significant fraction of the average equity and variance risk premia. In addition, Bollerslev, Todorov, and Xu (2015) find that the jump risk component of the variance risk premium helps predict market returns, whereas Bali, Cakici, and Chabi-Yo (2011) carry out a similar analysis using alternative risk-neutral and physical measures of riskiness. Siriwardane (2015) relies on the cross-section of equity option portfolios using a large number of firms to estimate daily measures of market-wide disaster risk. He finds that they are useful to predict economics downturns and to build profitable portfolios sorted by disaster risk exposure. The main shortcoming of these option-based estimates relates to data limitation, especially at the high frequency. Almeida, Ardison, Garcia, and Vicente (2017) show how to circumvent this issue by estimating a tail risk measure based on the risk-neutral excess expected shortfall of a cross-section of equity returns. Interestingly, they find that their equity tail risk measure helps predict both macroeconomic conditions and future market returns in the US.

We estimate ETR and HFTR measures from June 2002 to June 2015 using almost 200 stocks actively traded on B3 and over 6,800 investment funds in Brazil, respectively. Perhaps surprisingly, the tail risk measures exhibit very different behaviors, displaying little correlation among them. In particular, tail risk indicators under the physical distribution (PD) differ markedly from their risk-neutral (RN) counterparts. The AUM-weighted hedge-fund portfolio has significant contemporaneous exposure only to the ETR under the RN measure. In contrast, we find little evidence that Brazilian hedge funds load either on the ETR under the physical distribution or on the HFTR, regardless of whether under PD or RN, at the usual confidence levels.

Predictive regressions yield quite different results in that only HFTR_{RN} help forecast future hedge-fund returns up to 12 months ahead. However, HFTR_{RN} does not help to explain cross-sectional differences in expected returns. In turn, ETR measures fare poorly in the predictive dimension but have partial ability to explain cross-sectional expected hedge fund returns. Altogether, we conclude that the absence of heavy HFT activity compromises the overall exposure of the hedge fund industry to HFTR, but not the latter's ability to explain hedge fund returns over time. The high exposure of the AUM-weighted hedge-fund portfolio to ETR measures coupled with the partial ability of ETR measures in explaining cross-sectional returns reinforce that an important channel for exposure to hedge fund tail risk must be indeed based on high frequency trading.

The remainder of this paper is as follows. Section 2 describes the procedures to extract both equity and hedge fund tail risk measures, whereas Section 3 discusses the equity and hedge fund data we employ as well as the resulting tail risk measures. Section 4 examines tail risk exposures in the Brazilian hedge fund industry. Section 5 offers some concluding remarks.

2 Tail risk measures

To assess individual funds' tail risk exposure, Agarwal, Ruenzi, and Weigert (2017) measure tail dependence between their returns and the market return. They first compute tail sensitivity to the market return by means of

$$\mathrm{TS}_{i,t} = \lim_{q \to 0} \Pr\left(r_{i,t} \le F_{i,t}^{-1}(q) \,\middle|\, r_{m,t} \le F_{m,t}^{-1}(q)\right), \tag{1}$$

where $F_{i,t}$ and $F_{m,t}$ denote respectively the cumulative marginal distribution function of $r_{i,t}$ and $r_{m,t}$ at time t, and $q \in (0, 1)$ is the point in which we evaluate the distribution functions (say, $q = 0.05$). Funds with high tail sensitivity are likely to perform very poorly in bearish times, implying that market crashes affect these funds in particularly strong fashion. To account for severity, Agarwal, Ruenzi, and Weigert define the equity tail risk in the hedge fund industry as the cross-sectional average of the individual tail risks:

$$\mathrm{ETR}_{\mathrm{PD},t} = \frac{1}{N} \sum_{i=1}^{N} \mathrm{TS}_{i,t} \left| \frac{\mathrm{ES}_{i,t}}{\mathrm{ES}_{m,t}} \right|, \tag{2}$$

where $\mathrm{ES}_{i,t}$ and $\mathrm{ES}_{m,t}$ denote the expected shortfall of the fund return and of the market return at time t, respectively.

The reliance on expected shortfall is convenient because ES is a coherent measure of downside risk, as opposed to the more popular value-at-risk measure (Agarwal and Naik, 2004; Liang and Park, 2010)). Taking the individual-to-market ES ratio allows assessing hedge funds' tail risk exposure to equity risk market. In this paper, we also compute a HFTR version of Agarwal, Ruenzi, and Weigert's (2017) tail risk measure by substituting the returns on the value-weight portfolio of hedge funds for the market return in both (1) and (**??**). As in Agarwal, Ruenzi, and Weigert (2017), we employ 2 years of historical data to compute sample expected shortfalls, whereas we proxy the market portfolio by the value-weighted portfolio of the individual stocks in our sample.

To compute a tail risk measure under the risk-neutral distribution, we employ Almeida, Ardison, Garcia, and Vicente's (2017) estimator that averages the excess expected shortfall of individual returns under the risk neutral distribution:

$$TR_{\mathrm{RN},t} = \frac{1}{N}\sum_{i=1}^{N} \mathbf{E}^{\mathbb{Q}}\Big[(VaR_{\alpha}(R_{i,t}) - R_{i,t}) \;\Big|\; R_{i,t} \leq VaR_{\alpha}(R_{i,t})\Big] \tag{3}$$

where $\mathbb{Q}$ indicates the risk-neutral density and α is the value-at-risk (VaR) threshold.

To back out the risk-neutral distribution, we use the nonparametric approach put forth by Almeida and Garcia (2017). They find a family of stochastic discount factors (SDFs) that minimize convex functions defined in the space of possible and strictly positive SDFs in incomplete markets. By assuming constant short-term rate and homogeneous physical probabilities, they establish a mapping between SDFs and RN distributions. To obtain closed-form solutions, Almeida and Garcia (2017) constrain the convex function to the Cressie-Read family: $\phi_{\gamma}(m) = \frac{m^{\gamma+1} - a^{\gamma+1}}{\gamma(\gamma+1)}$. Accordingly, the tail risk estimate inherits the implied SDF dependence on the value of γ, which we set to $\gamma = -0.5$ as in Almeida, Ardison, Garcia, and Vicente (2017).[2]

We follow Almeida, Ardison, Garcia, and Vicente (2017) in entertaining a 30-day rolling window to estimate the monthly tail risk measure.[3] As each daily return represents a state of nature, we must consider less than 30 assets to leave some room for market incompleteness. To this end, we employ the first five principal components of the asset returns (either stocks or hedge funds) over the 30-day window. This is in line with Kozak, Nagel, and Santosh (2018), who document that a SDF based on a few principal components of asset returns is able to explain many market anomalies.

[2] Using returns and options data on the S&P 500, they show that $\gamma = -0.5$ entails a very similar SDF to the one implied by Backus, Chernov, and Zin's (2014) disaster model. In addition, Kitamura, Otsu, and Evdokimov (2013) show that a Cressie-Read loss function with $\gamma = -0.5$ is the most robust based on asymptotic perturbation criteria.

[3] This means that, if a given month has 20 trading days, the window would also use the last 10 trading days of the previous month, ensuring a smoother variation over time.

3 Data description and analysis

In this section, we first provide a brief overview of the regulatory environment in the Brazilian investment fund industry and then describe the data we employ. Lastly, we discuss the resulting tail risk estimates under both risk-neutral and physical distributions.

Investment funds in Brazil face regulation from the Brazilian Securities and Exchange Commission (CVM) as well as from a self-regulatory body, ANBIMA. There is no distinction between mutual funds and hedge funds as in the US, with every investment fund in Brazil falling under the same regulatory framework. Funds must submit to CVM daily reports with return, net assets, share value, and number of shareholders, as well as monthly reports with end-of-the-month portfolio holdings. The CVM website publishes the funds' daily information within at most two days after receiving the reports. See Varga and Wengert (2009) and Domingues (2012) for more details on the regulatory environment.

The above regulatory requirements work in our favor in that we observe the performance of the universe of investment funds in Brazil. The ANBIMA database is virtually free of the usual biases that plague hedge fund data.[4] There is no self-reporting bias because all investment funds must report to the CVM, regardless of their performance. Similarly, there is neither instant-history, nor survivorship bias in the ANBIMA database as it includes defunct funds as well. The other main advantage of using Brazilian investment fund data is the availability of daily returns. This is especially convenient for the estimation of tail risk exposures under the risk-neutral measure.

The ANBIMA database contains information about 16,654 active and defunct investment funds in Brazil from January 1997 to June 2015. The fund industry in Brazil has experienced a very substantial growth since 2000. In particular, total assets under management (AUM) increased from BRL$ 45 billion in 2000 to BRL$ 628 billion in 2015, with the number of funds rising from 1,200 in 2000 to over 7,000 in 2015. After restricting attention to open-end multi-market/strategy funds, we exclude from the sample every fund that essentially invests in other funds, such as Feeder and Mirror funds, investment funds in Fund Shares, Multi-Manager Investment Funds, and Fund of Funds, to avoid double counting. Finally, as we require daily data to estimate tail risk exposures under the risk-neutral measure, we also remove any fund for which we do not have access to daily

[4] See Fung and Hsieh (2004) for an excellent discussion on such biases in hedge fund databases.

share value. These filters reduce the sample to 6,823 hedge funds, of which 1,676 active and 5,147 defunct.

Table 1 provides an overview of the resulting sample. We report not only the number of funds that enters and exit the industry each year, but also the end-of-year total AUM, apart from basic descriptive statistics of the monthly percentage excess returns on the equal-weighted hedge fund portfolio. Between 2002 and 2005, the number of funds and AUM are essentially stable, with some consolidation in the industry: number of funds falls from 822 to 766, whereas total AUM grow from BRL$ 86.7 billion to BRL$ 111.9 billion. The share of dissolved funds to the total number of funds increases from 15%-20% to 50% in the beginning of 2005. As Brazil rides the commodity boom between 2006 and 2012, we observe a large expansion in the hedge fund industry, with the number of funds and total AUM increasing more than threefold to 2,256 and to BRL$ 411.8 billion, respectively. Finally, the Brazilian hedge fund industry stabilizes in the last few years of the sample, with about 2,500 funds managing approximately BRL$ 450 billion in assets.

Despite the substantial growth of the industry, the equal-weighted hedge fund portfolio does not exhibit a stellar performance. There are only three years between 2002 and 2015 in which excess return is positive. Apart from the very strong negative impact of the financial crisis in 2008, the presence of many defunct hedge funds in the sample obviously pushes down the average performance in the hedge fund industry. Further analysis indeed shows that the value-weighted hedge fund portfolio displays a much better performance (e.g., positive in 11 years), reflecting the fact that negative shocks affect funds with lower AUM in a relatively stronger manner.

It seems reasonable to wonder how much information hedge fund returns at the daily frequency convey given that they must mark to market every illiquid asset they trade. For instance, Choi, Kronlund, and Oh (2019) show that the net asset values of US bond mutual funds do not change on more than 30% of trading days, implying a large number of zero daily returns. Presumably, one should expect a higher proportion of zero daily returns for hedge funds trading on illiquid assets. As it turns out, the hedge fund returns in our sample are nonzero for more than 99,95% of the trading days.

We retrieve stock data from Bloomberg. The latter provides daily returns and traded volume for all stocks traded on B3. As most public firms in Brazil issue both common and preferred shares, we make sure to keep only the most liquid between them in order to ensure only one security per firm. We exclude Brazilian depositary receipts from the sample as well as any return resulting from a daily traded volume below BRL$ 20,000. Table 2 summarizes the number of stocks and average volume of monthly trade across the stocks in our sample for each year. In 2002, applying the above filters renders only 27 stocks in the sample. Apart from 2008, sample size grows monotonically until 2013. The number of stocks then falls from 142 to 130 in 2014. By the end of the sample period in June 2015, the cross section consists of 134 stocks (out of the 195 firms that appear in the sample). Traded volume exhibits a similar growth over time.

We next turn our attention to the resulting tail risk estimates. Figure 1 depicts the different equity and hedge fund tail risk measures. Moving from the physical to the risk-neutral distribution has a huge impact. First, tail risk estimates under the physical measure are much more persistent than the estimates under the risk-neutral measure. Second, the tail risk measures have peaks that seldom coincide, reflecting low correlations. Table 3 indeed confirms the latter. Interestingly, we find that the most sizable correlations (in magnitude) are across equity and hedge-fund markets: -0.644 between $\mathrm{ETR}_{\mathrm{PD}}$ and $\mathrm{HFTR}_{\mathrm{PD}}$, 0.548 between equity and hedge-fund returns, and 0.479 between $\mathrm{ETR}_{\mathrm{RN}}$ and $\mathrm{HFTR}_{\mathrm{PD}}$.

4 Which tail risk matters the most?

In this section, we present the results of the tail risk exposures of Brazilian hedge funds and compare their predictive power over time and cross-sectionally. First, we test the exposure of aggregate hedge-fund portfolios to the tail risk measures. Second, we test the predictability power of the tail risk measures. Third, we check if individual fund exposure to tail risk helps explain the cross-sectional dispersion in hedge funds returns.

4.1 Tail risk exposures

We examine the exposure of hedge funds to tail risk estimates using time-series regressions with and without other conventional risk factors as controls. In particular, we employ a wide array of risk factors in the literature. First, we collect the Fama-French factors (market return, SMB and HML) for the Brazilian market from the Center for Research in Financial Economics of the University of São Paulo (NEFIN/USP). Second, we consider changes in the Brazilian 5-year nominal government bond yield (ΔBZ5Y) given that the extremely high interest rates in Brazil should substantially affect the positions of Brazilian hedge funds. Third, we entertain Fung and Hsieh (2004) factors for hedge fund returns in the US, including the changes in the 10-year US treasury bond yield (ΔUS10Y), credit spread between BBB and AAA corporate bond yields and trend-following straddle portfolios for bonds, currency, commodity, interest rate, and stock markets (PTXSBD, PTFSFX, PTFSCOM, PTFSIR and PTFSSTK, respectively), as well as the changes in the CBOE volatility index (ΔVIX) as in Bakshi, Kapadia, and Madan (2003). We do not use other higher-order risk-neutral moment factors because of their much shorter time-span availability. We nonetheless have to shorten our sample period to between June 2002 and June 2015.

Table 4 documents the risk exposure estimates of the equal-weighted portfolio of hedge funds.[5] In the first regression, we assess hedge funds' exposures to the extant risk factors in the literature. The only significant risk exposures are to the market return, SMB, $\Delta BZ5Y$ and ΔVIX, with estimates statistically different from zero at the 1% confidence level. This finding is not unexpected given that every insignificant risk exposure refers to factors from the US economy. Although the VIX index corresponds to the options-implied volatility of the S&P500 index, it is a well-established fear gauge—and hence of investors' risk appetite—in global markets.

We next regress the equal-weighted hedge fund returns on each tail-risk measure, controlling for the above risk factors. For ease of comparison, we normalize every tail-risk measure to have zero mean and unit standard deviation. Table 4 reveals no evidence of tail-risk exposure in the hedge fund industry.

Figure **??** indicates that there is heavy concentration in the Brazilian hedge fund industry in that few funds are responsible for most of the asset under management (AUM). It is thus important to examine what happens if we rely instead on AUM-weighted hedge fund returns. Table 5 unveils that larger hedge funds seem to load less on Brazilian small caps given that the exposure to SMB becomes insignificant at the usual confidence levels. As a result, the only significant exposures to Brazilian-specific factors are to the equity market returns and to the changes in the Brazilian 5-year nominal government bond yield. In contrast, the investment opportunity sets of larger hedge funds seem to depend more on US factors. The AUM-weighted returns load significantly on fixed-income

[5] Adding lagged factors and a MA component as in Getmansky, Lo, and Makarov (2004) to control for liquidity does not change the qualitative findings. These results are available from the authors upon request.

trend-following factors—positively on PTFSBD and negatively on PTFSIR—at the 1% level, as well as on the changes in the 10-year T-bond yield and on ΔVIX at 5% and 10% confidence levels, respectively.

As before, adding equity and hedge-fund tail-risk measures either individually or jointly have little effect on the exposures to the conventional risk factors. We find that the AUM-weighted returns on hedge funds have significantly positive loadings on $\mathrm{ETR}_{\mathrm{RN}}$ at the 10% level. In particular, a one standard deviation shock to $\mathrm{ETR}_{\mathrm{RN}}$ increases by 0.197% the return on the AUM-weighted portfolio.

In the next section, we investigate whether tail risk measures also help predict future hedge-fund returns. As before, we carry out the analysis with and without additional risk factors to assess the marginal gains in predictive ability.

4.2 Predictive power of tail risk measures

To examine their forward-looking information content, we consider the following predictive regressions:

$$EW_{t,t+k} = \alpha + \beta_j TR_{j,t} + \lambda' RF_t + \rho EW_{t-k,t} + \epsilon_t, \tag{4}$$

where $EW_{t,t+k}$ is the return on the equal-weighted portfolio between t and $t+k$, $TR_{j,t}$ is the jth tail-risk measure on month t, with $j \in \{\mathrm{PD}, \mathrm{RN}\}$, RF_t is the vector of additional risk factors on month t, and $EW_{t-k,t}$ is the past k-month return on the equal-weighted portfolio. Table 6 documents the estimation results with k ranging from 1 to 12.

Disregarding additional risk factors, equity-based tail risk measures are poor predictors of future hedge-funds returns, with insignificant coefficient estimates at the usual confidence levels for any horizon. In contrast, the hedge-fund tail risk measure under the RN distribution yields good predictive power. It seems to affect the steepness of the term structure of expected returns in that it has opposite effects on the short- and long-ends, with little impact on mid horizons. Findings are very similar if we control for extant risk factors in the literature.

Our empirical findings are in line with Almeida, Fernandes, Santos, and Valente's (2016) in that $\mathrm{HFTR}_{\mathrm{RN}}$ entail better forecasting ability than their equity tail risk counterparts. We nonetheless find disappointing results for both equity and hedge-fund tail risk measures under the physical distribution (HFTR_{PD} and HFTR_{PD}). We deem that their discouraging performance is at least partly due to the clearly much higher persistence they exhibit in Figure 1.

To validate the predictive ability of the tail risk measures, we employ the robust resampling test by Camponovo, Scaillet, and Trojani (2014) to check whether a few extreme observations are hiding any predictability pattern. The approach is fully data-driven, resting on robust weighted least-squares and resampling-based confidence intervals. For each 120-month window, we run a predictive regression and build the 95% confidence intervals for the coefficient estimates of the tail risk measures. Figures 3 and 4 depict the rolling pointwise estimates and their 95% confidence intervals for the 1- and 12-month returns on the equal-weighted hedge-fund portfolio, respectively.

At the short horizon, we find that the coefficient estimates of HFTR_{RN} are most of the time significant at the 5% level, whereas the coefficient estimates of ETR_{PD} become significantly positive only by the end of the sample period. At the 12-month horizon, the above hedge-fund tail risk measures remain significant virtually at every point in time. This is in stark contrast with every other tail risk measure, including ETR_{PD}, whose coefficient estimates are never statistically different from zero at the 5% level. Finally, it is worth stressing that the signs of the coefficient estimates of the tail risk measures match those in Table 6, including the evidence that HFTR_{RN} entails a negative effect at the 1-month horizon, but a positive effect at the 12-month horizon.

Our findings so far reveal that hedge-fund tail risk measures help predict aggregate returns on the hedge fund industry relatively more than the equity tail risk indicators, as in Almeida, Fernandes, Santos, and Valente (2016). In the next section, we assess whether the same holds on the cross-section of hedge-fund returns.

4.3 Cross-sectional predictive power

We now evaluate whether hedge-fund exposure to tail risk factors is able to predict cross-sectional differences in hedge fund expected returns. We perform a portfolio-level analysis to test the cross-sectional predictive power of each tail risk exposure. In particular, we estimate time-series regressions of individual hedge-fund excess returns on tail risk measures over a 120-month rolling-window period from June 2002 to June 2015. For each 10-year window, we organize the funds in quintiles according to their exposures to each tail risk indicator. Accordingly, the first quintile contains the hedge funds with least exposure, whereas we place the funds with highest exposures in the fifth quintile. Tables 7 and 8 report the average next-month excess (risk-adjusted) return for each ETR- and HFTR-sorted quintile portfolios, with their Newey-West t-statistics in parentheses.

Exposure to $\mathrm{HFTR}_{\mathrm{PD}}$ and $\mathrm{HFTR}_{\mathrm{RN}}$ do not seem to explain much of the cross-sectional differences in hedge fund (risk-adjusted) returns, whereas we observe a strongly monotonic pattern in the alphas of the higher-dimensional factor models across the quintiles sorted by their equity tail risk counterparts. This pattern is increasing for $\mathrm{ETR}_{\mathrm{RN}}$, but decreasing for $\mathrm{ETR}_{\mathrm{PD}}$, suggesting that some sort of tail risk premium must be significant in the Brazilian equity market inducing such different results for physical versus risk-neutral tail risk[6]. The ability of equity tail risk to explain the cross section of expected hedge fund returns is in line with Jiang and Kelly (2012) who report evidence that hedge funds entail substantial exposure to equity tail risk (ETR).

5 Conclusion

In this paper we compare the ability of different tail risk measures to explain the time series and cross-section variation in hedge fund returns. The main novelty is that we rely on a unique data set with daily returns for every hedge fund in Brazil (dead or alive), which allows for the estimation of monthly tail risk measures based on expected shortfall that are infeasible for the US and European markets.

We examine the contemporaneous exposure of hedge-fund index returns to these tail risk measures as well as their ability not only to predict future hedge-fund index returns but also to to explain the cross-section of expected hedge-fund returns. Despite non-negligible differences across different tail risk measures, they all matter in at least one of the above metrics. While hedge funds contemporaneous load significantly on equity tail risk, which is also important to explain the cross section of hedge fund returns, exposure to hedge-fund tail risk displays better predictive ability in the time series dimension.

[6]Nonetheless, It is hard to determine the exact structure of tail risk premium from this analisys since the two equity-based tail risk measures are derived from different methodologies.

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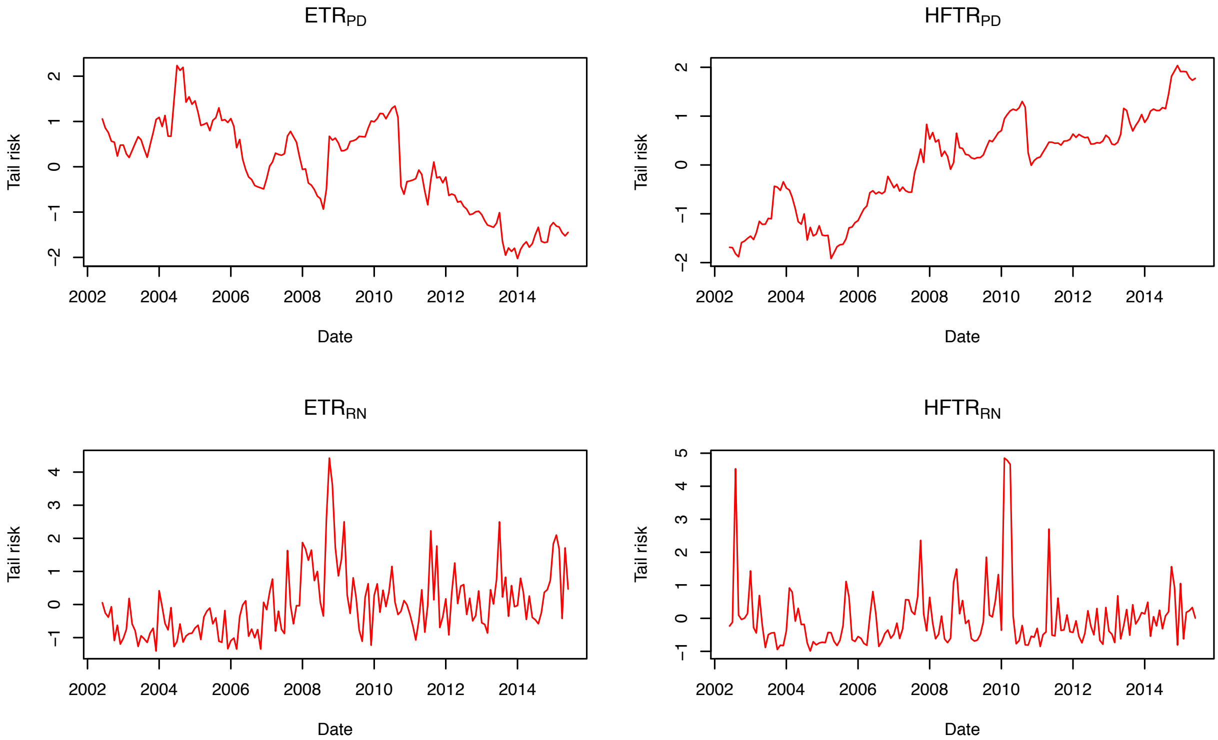

Figure 1: Equity and hedge-fund tail risk estimates between June 2002 to June 2015

ETR and HFTR denote equity and hedge-fund tail risk measures based on the expected shortfall either under the physical distribution(PD) or under the risk-neutral distribution (RN).

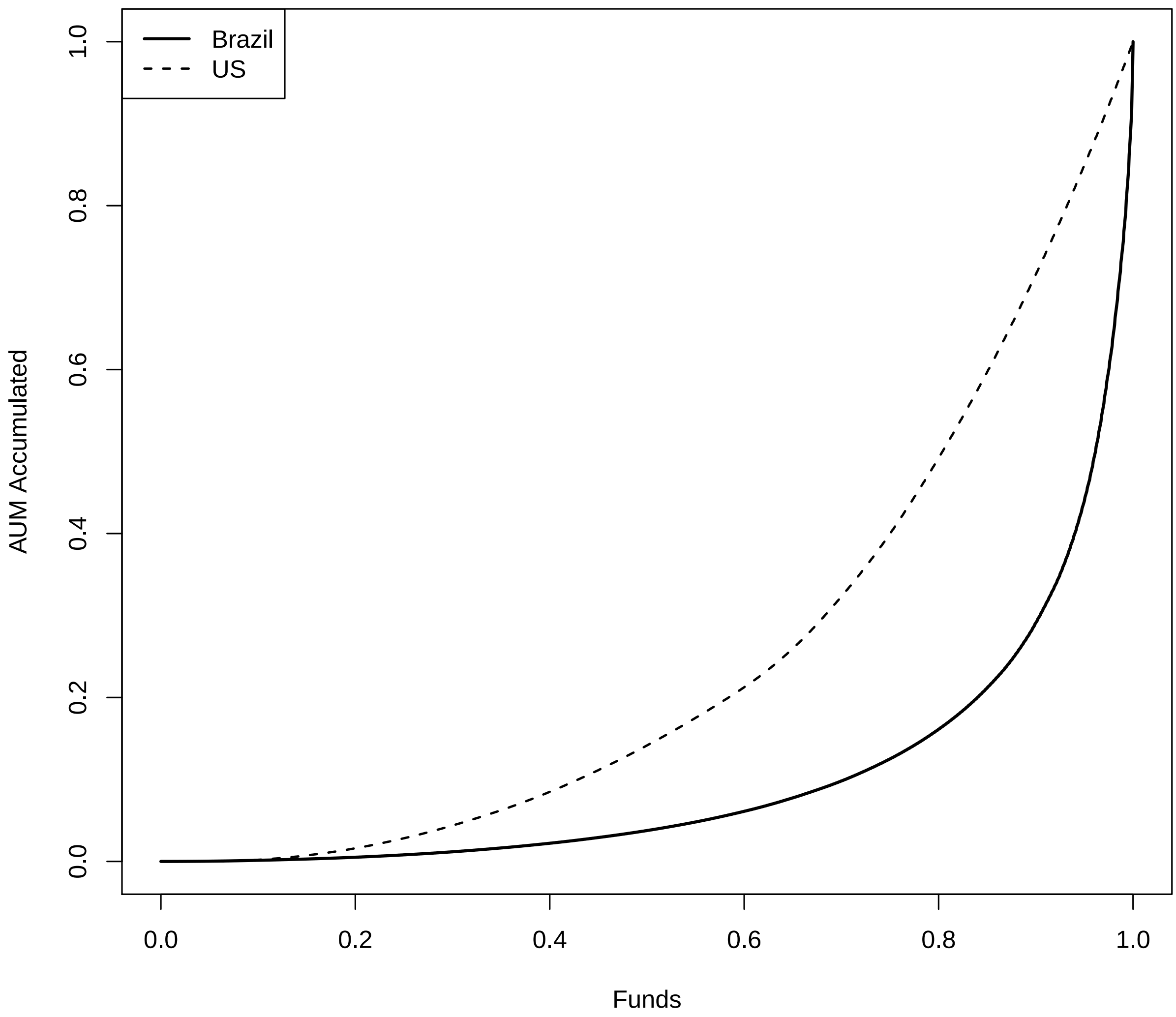

Figure 2: Concentration in the hedge fund industry: Brazil vs US in 2013

Data source is ANBIMA for Brazil and Barclay Hedge for the US.

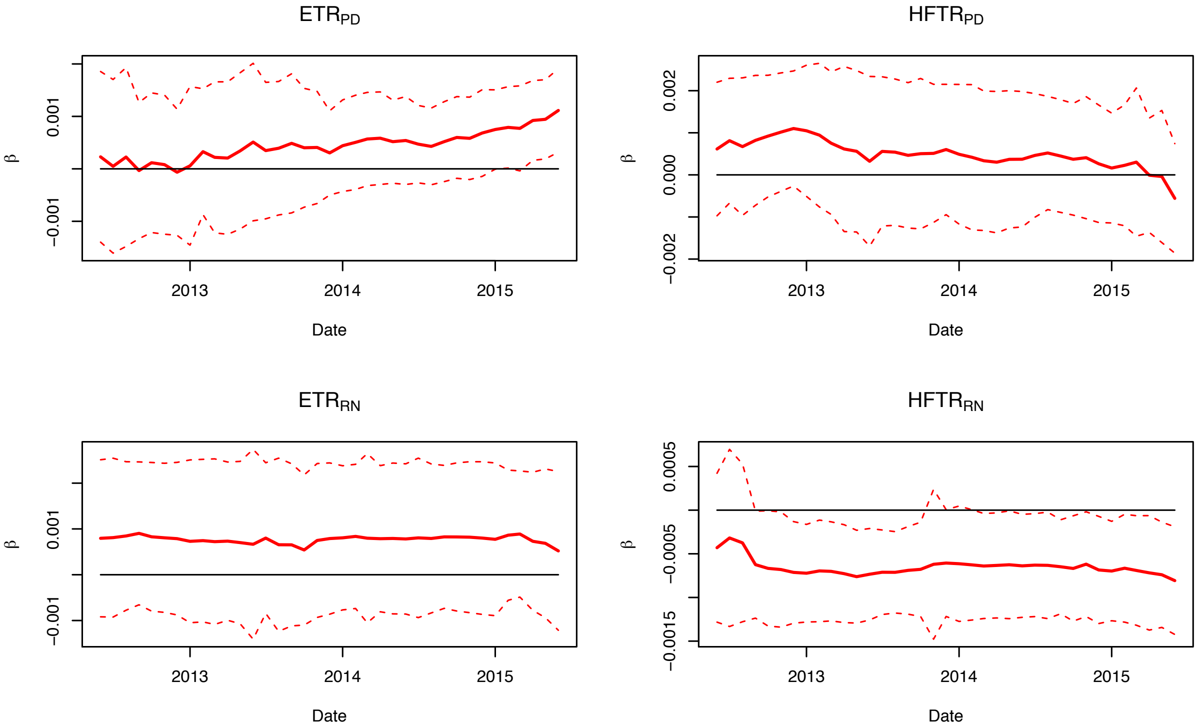

Figure 3: Predictive regressions with tail risk measures, 1-month horizon

We plot the coefficient estimates of the tail risk measures (solid lines) and their robust 95% confidence interval (dotted lines) in the predictive regressions. For each 120-month estimation window, we regress the excess return on the equal-weighted hedge fund index at $t+1$ on a given tail risk measure at t, controlling for the the past excess return on the equal-weighted index at t.

Figure 4: Predictive regressions with tail risk measures, 12-month horizon

We plot the coefficient estimates of the tail risk measures (solid lines) and their 95% robust confidence interval (dotted lines) in the predictive regressions. For each 120-month estimation window, we regress the excess 12-month return on the equal-weighted hedge fund index at $t + 12$ on a given tail risk measure at t, controlling for the the past excess 12-month return on the equal-weighted index at t.

Table 1: Descriptive statistics of the ANBIMA hedge-fund data

year	number of funds				total AUM	equal-weighted hedge-fund index monthly returns (%)				
	initial	entry	exit	final	(BRL$ billion)	mean	median	standard deviation	minimum	maximum
2002	805	171	154	822	86.73	0.33	0.28	0.89	-0.87	1.81
2003	826	275	172	929	134.34	-0.23	-0.01	0.74	-1.63	0.57
2004	930	237	200	967	164.63	-0.16	-0.10	0.22	-0.58	0.15
2005	965	301	500	766	111.90	-0.43	-0.34	0.55	-1.60	0.59
2006	763	292	126	929	190.47	-0.09	-0.02	0.46	-1.25	0.42
2007	930	375	140	1165	249.52	-0.10	-0.04	0.43	-0.71	0.50
2008	1163	430	271	1322	246.52	-0.55	-0.74	1.22	-3.43	0.94
2009	1321	442	264	1499	306.50	0.23	0.30	0.30	-0.29	0.66
2010	1497	520	218	1799	368.75	-0.08	-0.15	0.46	-0.90	0.71
2011	1798	563	257	2104	355.76	-0.30	-0.17	0.67	-1.66	1.03
2012	2102	528	374	2256	411.79	0.03	0.16	0.46	-1.00	0.51
2013	2272	591	456	2407	423.54	-0.38	-0.39	0.46	-1.37	0.29
2014	2462	506	462	2506	444.55	-0.29	-0.36	0.45	-1.17	0.31
2015	2504	203	200	2507	477.77	-0.12	0.09	0.73	-1.02	0.76

The sample period runs from June 2002 to June 2015.

Table 2: Descriptive statistics of the Bloomberg equity data

year	number of stocks				average monthly volume (BRL$ billion)
	initial	entry	exit	final	
2002	27	5	5	27	1.30
2003	27	13	0	40	1.35
2004	40	9	3	46	1.57
2005	46	9	3	52	1.73
2006	52	16	0	68	2.00
2007	68	49	5	112	3.05
2008	112	5	22	95	3.94
2009	95	30	6	119	4.28
2010	119	18	15	122	4.34
2011	122	15	13	124	4.94
2012	124	17	5	136	5.74
2013	136	13	7	142	6.56
2014	142	8	20	130	6.58
2015	130	10	6	134	7.15

The sample period runs from June 2002 to June 2015.

Table 3: Correlations between tail risks and market/industry returns

	ETR_{PD}	$HFTR_{PD}$	ETR_{RN}	$HFTR_{RN}$	HF(EW)
$HFTR_{PD}$	-0.644				
ETR_{RN}	-0.255	0.479			
$HFTR_{RN}$	0.069	0.164	0.157		
HF(EW)	0.108	-0.046	-0.149	-0.146	
market return	0.159	-0.097	-0.267	-0.072	0.548

ETR and HFTR denote equity and hedge-fund tail risk measures, with subscripts PD and RN referring to the physical and risk-neutral distributions, respectively. HF(EW) refers to the monthly return on the equal-weighted hedge-fund index, whereas market return corresponds to the excess return on the Brazilian (equity) market portfolio. The sample period is from June 2002 to June 2015.

Table 4: Risk exposures of the equal-weighted hedge-fund index returns

	(1)	(2)	(3)	(4)	(5)	(6)
market return	4.493***	4.438***	4.515***	4.689***	4.476***	4.567***
	(0.783)	(0.801)	(0.790)	(0.792)	(0.785)	(0.806)
HML	−1.156	−1.191	−1.128	−1.157	−1.136	−1.222
	(0.966)	(0.974)	(0.975)	(0.963)	(0.969)	(0.974)
SMB	2.116***	2.048**	2.147***	2.284***	2.043**	2.021**
	(0.807)	(0.832)	(0.819)	(0.813)	(0.817)	(0.849)
ΔBZ5Y	0.071***	0.071***	0.072***	0.071***	0.070***	0.069***
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
ΔUS10Y	−0.207	−0.200	−0.209	−0.236	−0.220	−0.244
	(0.190)	(0.192)	(0.191)	(0.190)	(0.191)	(0.193)
credit spread	−0.245	−0.244	−0.249	−0.331	−0.500	−0.363
	(0.217)	(0.218)	(0.219)	(0.225)	(0.218)	(0.228)
PTFSBD	0.483	0.490	0.478	0.394	0.481	0.385
	(0.302)	(0.304)	(0.304)	(0.308)	(0.303)	(0.310)
PTFSFX	−0.176	−0.186	−0.172	−0.128	−0.175	−0.135
	(0.216)	(0.218)	(0.217)	(0.218)	(0.216)	(0.220)
PTSFCOM	−0.187	−0.179	−0.191	−0.200	−0.196	−0.195
	(0.268)	(0.270)	(0.269)	(0.267)	0.269	0.270
PTFSIR	−0.173	−0.183	−0.168	−0.220	−0.170	−0.261
	(0.155)	(0.159)	(0.156)	(0.158)	(0.155)	(0.166)
PTFSSTK	0.025	0.032	0.026	−0.024	0.022	−0.023
	(0.321)	(0.323)	(0.322)	(0.322)	(0.322)	(0.324)
ΔVIX	−0.035***	−0.035***	−0.035***	−0.031***	−0.034***	−0.031***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
ETR_{PD}		0.014				0.040
		(0.040)				(0.044)
$HFTR_{PD}$			0.010			0.012
			(0.038)			(0.040)
ETR_{RN}				0.063		0.081*
				(0.044)		(0.047)
$HFTR_{RN}$					−0.024	−0.034
					(0.037)	(0.038)
constant	−0.171***	−0.171***	−0.171***	−0.178***	−0.172***	−0.179***
	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)
Adjusted R^2	0.475	0.472	0.472	0.479	0.473	0.526

We report the least-squares estimates (×100) of time series regressions of the equal-weighted hedge-fund index returns on risk factors, as well as their Newey-West standard errors within parentheses. We denote by *, ** and *** statistical significance at the 10%, 5% and 1% levels. The sample runs from June 2002 ro June 2015, amounting to 157 monthly observations.

Table 5: Risk exposures of the AUM-weighted hedge-fund index returns

	(1)	(2)	(3)	(4)	(5)	(6)
market return	$3.141^{\star\star}$	$2.942^{\star\star}$	$3.018^{\star\star}$	$3.555^{\star\star\star}$	$3.162^{\star\star}$	$3.113^{\star\star}$
	(1.323)	(1.351)	(1.332)	(1.332)	(1.327)	(1.357)
HML	0.457	0.330	0.302	0.454	0.432	0.233
	(1.633)	(1.644)	(1.645)	(1.620)	(1.638)	(1.638)
SMB	−0.516	−0.759	−0.691	−0.161	−0.427	−0.451
	(1.364)	(1.404)	(1.381)	(1.368)	(1.381)	(1.428)
ΔBZ5Y	$0.137^{\star\star\star}$	$0.137^{\star\star\star}$	$0.139^{\star\star\star}$	$0.136^{\star\star\star}$	$0.136^{\star\star\star}$	$0.134^{\star\star\star}$
	(0.029)	(0.028)	(0.029)	(0.029)	(0.029)	(0.029)
ΔUS10Y	$-0.646^{\star\star}$	$-0.620^{\star}$	$-0.636^{\star\star}$	$-0.706^{\star\star}$	$-0.630^{\star}$	$-0.671^{\star\star}$
	(0.321)	(0.324)	(0.322)	(0.320)	(0.324)	(0.325)
credit spread	−0.225	−0.222	−0.205	−0.405	−0.219	−0.423
	(0.367)	(0.368)	(0.369)	(0.378)	(0.369)	(0.384)
PTFSBD	$1.337^{\star\star\star}$	$1.361^{\star\star\star}$	$1.367^{\star\star\star}$	$1.148^{\star\star}$	$1.340^{\star\star\star}$	$1.155^{\star\star}$
	(0.511)	(0.513)	(0.513)	(0.518)	(0.513)	(0.521)
PTFSFX	−0.316	−0.216	−0.316	−0.352	−0.337	−0.263
	(0.365)	(0.366)	(0.366)	(0.368)	(0.366)	(0.371)
PTSFCOM	0.065	0.095	0.086	0.038	0.076	0.080
	(0.453)	(0.455)	(0.454)	(0.450)	(0.455)	(0.454)
PTFSIR	$-0.756^{\star\star\star}$	$-0.795^{\star\star\star}$	$-0.779^{\star\star\star}$	$-0.856^{\star\star\star}$	$-0.759^{\star\star\star}$	$-0.933^{\star\star\star}$
	(0.262)	(0.268)	(0.264)	(0.266)	(0.263)	(0.279)
PTFSSTK	0.441	0.465	0.434	0.337	0.444	0.356
	(0.543)	(0.544)	(0.543)	(0.542)	(0.544)	(0.545)
ΔVIX	$-0.031^{\star}$	$-0.032^{\star}$	$-0.032^{\star}$	−0.023	$-0.031^{\star}$	−0.024
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.019)
ETR_{PD}		0.050				0.077
		(0.067)				(0.075)
HFTR_{PD}			−0.054			−0.012
			(0.064)			(0.067)
ETR_{RN}				$0.133^{\star}$		$0.153^{\star}$
				(0.073)		(0.079)
HFTR_{RN}					0.029	0.004
					(0.062)	(0.064)
constant	$0.167^{\star\star}$	$0.169^{\star\star}$	$0.167^{\star\star}$	$0.153^{\star\star}$	$0.167^{\star\star}$	$0.153^{\star\star}$
	(0.067)	(0.068)	(0.068)	(0.067)	(0.068)	(0.068)
Adjusted R^2	0.217	0.215	0.216	0.229	0.213	0.221

We report the least-squares estimates (×100) of time series regressions of the AUM-weighted hedge-fund index returns on risk factors, as well as their Newey-West standard errors within parentheses. We denote by *, ** and *** statistical significance at the 10%, 5% and 1% levels. The sample runs from June 2002 ro June 2015, amounting to 157 monthly observations.

Table 6: Predictive regressions for equal-weighted hedge-fund index returns, with and without extant risk factors as controls

horizon	ETR_{PD}		$HFTR_{PD}$		ETR_{RN}		$HFTR_{RN}$	
(in months)	without	with	without	with	without	with	without	with
1	0.072 (1.640)	0.065 (1.288)	0.013 (0.208)	0.037 (0.547)	−0.011 (−0.188)	−0.002 (−0.046)	−0.089 (−2.832)	−0.077 (−2.997)
2	0.137 (1.130)	0.113 (1.054)	0.046 (0.318)	0.069 (0.556)	0.090 (0.978)	0.063 (0.659)	−0.114 (−2.088)	−0.104 (−1.946)
3	0.196 (1.058)	0.136 (0.939)	0.043 (0.182)	0.106 (0.580)	0.171 (1.282)	0.181 (1.423)	−0.024 (−0.213)	0.000 (0.000)
4	0.041 (0.120)	0.118 (0.455)	0.103 (0.516)	0.109 (0.544)	−0.000 (−0.002)	0.040 (0.362)		
5	0.307 (0.874)	0.268 (1.074)	0.056 (0.122)	0.115 (0.341)	0.115 (0.510)	0.145 (0.585)	0.074 (0.615)	0.118 (1.122)
6	0.363 (0.936)	0.327 (1.071)	0.036 (0.068)	0.093 (0.219)	0.126 (0.495)	0.130 (0.433)	0.127 (0.981)	0.170 (1.562)
7	0.394 (0.905)	0.354 (1.012)	0.019 (0.031)	0.077 (0.160)	0.105 (0.328)	0.164 (0.507)	0.204 (1.276)	0.251 (1.883)
8	0.411 (0.759)	0.382 (0.941)	0.022 (0.029)	0.054 (0.099)	0.119 (0.338)	0.183 (0.537)	0.238 (1.323)	0.296 (2.207)
9	0.423 (0.741)	0.383 (0.898)	0.014 (0.016)	0.044 (0.076)	0.077 (0.190)	0.134 (0.377)	0.251 (1.415)	0.312 (2.105)
10	0.436 (0.766)	0.379 (0.828)	−0.007 (−0.009)	0.069 (0.112)	0.021 (0.039)	0.118 (0.313)	0.339 (2.086)	0.406 (2.625)
11	0.447 (0.733)	0.400 (0.834)	−0.007 (−0.007)	0.094 (0.153)	0.048 (0.110)	0.160 (0.444)	0.363 (2.340)	0.442 (3.074)
12	0.451 (0.732)	0.421 (0.840)	−0.029 (−0.030)	0.056 (0.083)	0.036 (0.089)	0.155 (0.440)	0.331 (1.568)	0.405 (2.243)

We report the least-squares estimates of the tail risk coefficient estimates in predictive regressions for k-month equal-weighted hedge-fund index returns, with and without the extant risk factors as additional controls. We also display the Newey-West t-statistics within parentheses. The sample period runs from June 2002 to June 2015.

Table 7: Portfolio sorts on equity tail-risk exposures

ETR	risk-adjustment	Q_1	Q_2	Q_3	Q_4	Q_5	$Q_5 - Q_1$
PD	none	0.001	−0.024	−0.092	−0.123	−0.298	−0.299
		(0.008)	(−0.726)	(−2.674)	(−2.029)	(−1.437)	(−1.748)
	Fama-French factors	0.040	−0.007	−0.094	−0.119	−0.316	−0.355
		(0.457)	(−0.205)	(−1.976)	(−1.782)	(−1.561)	(−2.280)
	above + ΔBZ5Y	0.043	−0.009	−0.091	−0.120	−0.324	−0.368
		(0.489)	(−0.233)	(−2.035)	(−1.815)	(−1.610)	(−2.340)
	above + Fung-Hsieh factors	0.165	0.002	−0.081	−0.159	−0.423	−0.588
		(1.895)	(0.049)	(−2.026)	(−1.662)	(−1.869)	(−2.762)
	above + ΔVIX	0.165	0.005	−0.074	−0.148	−0.426	−0.591
		(1.912)	(0.123)	(−1.766)	(−1.619)	(−1.881)	(−2.882)
RN	none	−0.344	−0.142	−0.105	−0.028	−0.106	0.237
		(−1.426)	(−1.782)	(−1.593)	(−1.209)	(−1.170)	(1.201)
	Fama-French factors	−0.403	−0.115	−0.130	−0.020	−0.114	0.289
		(−1.471)	(−1.246)	(−1.475)	(−0.752)	(−0.976)	(1.346)
	above + ΔBZ5Y	−0.398	−0.117	−0.129	−0.020	−0.118	0.280
		(−1.473)	(−1.254)	(−1.502)	(−0.755)	(−1.007)	(1.249)
	above + Fung-Hsieh factors	−0.593	−0.206	−0.142	−0.042	−0.048	0.546
		(−2.202)	(−1.673)	(−2.069)	(−0.688)	(−0.527)	(2.394)
	above + ΔVIX	−0.560	−0.214	−0.124	−0.031	0.007	0.567
		(−2.217)	(−2.015)	(−2.044)	(−0.455)	(0.096)	(2.434)

For each month between June 2002 and June 2015, we sort hedge funds by their exposure to equity tail risk and then track the average performance in each quintile (equal-weighted) portfolio in the next month. Apart from average portfolio returns, we also consider alpha measures of performance that adjust returns by their exposure to the risk factors in the second column. Newey-West t-statistics are within parentheses.

Table 8: Portfolio sorts on hedge-fund tail risk exposures

HFTR	risk-adjustment	Q_1	Q_2	Q_3	Q_4	Q_5	$Q_5 - Q_1$
PD	none	−0.233	−0.090	−0.037	−0.017	−0.157	0.076
		(−1.325)	(−1.258)	(−0.890)	(−0.656)	(−1.540)	(0.523)
	Fama-French factors	−0.255	−0.072	−0.026	−0.012	−0.126	0.129
		(−1.484)	(−0.997)	(−0.560)	(−0.380)	(−0.998)	(0.880)
	above + ΔBZ5Y	−0.267	−0.072	−0.024	−0.011	−0.121	0.146
		(−1.577)	(−0.984)	(−0.518)	(−0.362)	(−0.964)	(0.998)
	above + Fung-Hsieh factors	−0.294	−0.153	0.013	−0.009	−0.053	0.241
		(−1.351)	(−1.829)	(0.309)	(−0.273)	(−0.526)	(1.143)
	above + ΔVIX	−0.297	−0.150	0.021	−0.005	−0.047	0.251
		(−1.356)	(−1.781)	(0.537)	(−0.169)	(−0.474)	(1.195)
RN	none	−0.317	−0.039	−0.054	−0.062	−0.063	0.254
		(−1.954)	(−0.619)	(−1.032)	(−1.790)	(−0.534)	(1.847)
	Fama-French factors	−0.321	−0.018	−0.038	−0.063	−0.052	0.269
		(−1.927)	(−0.267)	(−0.705)	(−1.485)	(−0.402)	(1.721)
	above + ΔBZ5Y	−0.328	−0.020	−0.041	−0.062	−0.044	0.284
		(−1.924)	(−0.314)	(−0.754)	(−1.448)	(−0.341)	(1.640)
	above + Fung-Hsieh factors	−0.296	0.028	−0.049	−0.032	−0.143	0.153
		(−1.816)	(0.394)	(−0.883)	(−0.899)	(−0.746)	(0.946)
	above + ΔVIX	−0.299	0.029	−0.047	−0.025	−0.133	0.166
		(−1.870)	(0.419)	(−0.856)	(−0.671)	(−0.731)	(1.002)

For each month between June 2002 and June 2015, we sort hedge funds by their exposure to hedge-fund tail risk and then track the average performance in each quintile (equal-weighted) portfolio in the next month. Apart from average portfolio returns, we also consider alpha measures of performance that adjust returns by their exposure to the risk factors in the second column. Newey-West t-statistics are within parentheses.