Tailing tail risk in the hedge fund industry

Walter Distaso  
Imperial College Business School

Marcelo Fernandes  
Queen Mary University of London

Filip Zikes  
Imperial College Business School

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Abstract: This paper aims to assess dynamic tail risk exposure in the hedge fund sector. In particular, we model lower-tail dependence between hedge funds, bond, commodity, foreign exchange, and equity markets as a function of market uncertainty. We proxy the latter by means of a single index that combines the options-implied market volatility, the volatility risk premium, and the term spread. We find substantial time-variation in tail dependence even for hedge-fund styles that exhibit little unconditional tail dependence. This illustrates well the pitfalls of confining attention to unconditional measures of tail risk. In addition, tail dependence between hedge fund and equity market returns decreases significantly with both measures of market uncertainty, alleviating thus the likelihood of financial contagion. The only styles that feature neither unconditional nor conditional tail dependence are convertible arbitrage and equity market neutral. We also fail to observe any tail dependence with bond and currency markets, though we find strong evidence that the tail risk exposure of macro hedge funds to commodity markets increases with uncertainty. Our results are very robust to changes in the specific measure of tail dependence as well as in the factors that drive tail dependence. In addition, specification tests confirm that our semiparametric model not only fits very well the lower tails but also entail coefficient estimates that are very stable over time.

Keywords: copula, dynamic risk exposure, fat tail risk, hedge funds, market uncertainty, tail dependence, VIX, volatility risk premium.

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1 Introduction

The value of assets under management in the hedge fund industry has increased from $50 billion in 1990 to around $1.9 trillion in October 2007. This exponential growth is essentially due to the fact that hedge funds entail relatively high expected returns with low volatility. In addition, the (unconditional) correlation between the returns on hedge funds and on traditional asset classes (or risk factors) is also weak. Most hedge funds claim that this results from their ability to carrying uncorrelated incremental returns (or alpha) among different asset classes.

Since October 2007, the hedge fund sector has witnessed a gradual outflow of funds under management that substantially accelerated as of September 2008. By December 2008, the total assets under management reported by Hedge Fund Research Inc. plummeted to about 0.7 trillion, amounting to a drop of more than 60% from its all time peak. Over the same period, the HFRI composite index, which comprises a large cross-section of hedge funds, lost around 20% of its value. Still, this is considerably less than the 40% drop in the value of the S&P500 index.

This leads to the important question of whether there are diversification gains resulting from investments in hedge funds. An unconditional correlation-based analysis, which captures the amount of linear association between returns, can only partially address this question. Hedge funds typically engage into derivatives trading, short selling, and positions on illiquid assets, resulting in returns with serial correlation, negative skewness, excess kurtosis, and other option-like (nonlinear) features. See, among others, Fung and Hsieh (2001), Mitchell and Pulvino (2001), Amin and Kat (2003), Dor, Jagannathan, and Meier (2003), Getmansky, Lo, and Makarov (2004), Diez de los Rios and Garcia (2006), and Agarwal, Bakshi, and Huij (2008).

There is also evidence that hedge-fund trading strategies yield payoffs that are concave to some of the usual benchmarks. This means that the correlation between hedge-fund and broad-market returns is likely to rise in periods of financial distress (Edwards and Caglayan, 2001; Agarwal and Naik, 2004). As a matter of fact, the correlation between the HFRI Composite index and the S&P500 monthly returns has been about twice as high

\[^1\] For instance, Ribeiro and Veronesi (2002) develop a rational expectations equilibrium model in which news becomes more informative about the true state of the economy in bad times and hence the cross-market correlations increase.
in down markets (70%) than in up markets (34.5%) during the period 1990-2008.

To evaluate whether hedge funds indeed bring about diversification benefits, it does not suffice then to consider how their returns correlate with traditional asset classes (or the usual risk factors). One must also gauge how hedge fund returns co-vary with broad-market returns in extreme situations. In order to accomplish this, we resort to the concept of tail risk so as to measure the risk exposure of hedge funds in periods of market downturn. In this way, we assess diversification gains when markets experience large and negative returns, that is to say, at times they are needed most for the investors’ marginal utility of wealth is high.

Focusing on tail risk is also convenient for two reasons. First, it accommodates in a natural manner investors’ preferences concerning higher-order moments such as, e.g., skewness and kurtosis (Scott and Horvath, 1980; Pratt and Zeckhauser, 1987). This is important since, as Agarwal, Bakshi, and Huij (2008) show, hedge funds have substantial exposure to higher-order moments risks. The corresponding premia are indeed economically significant, playing an important role in explaining hedge funds’ returns. The exposures to these factors should be taken into account when evaluating hedge funds’ performance. Second, it does not impose a symmetric dependence structure in the tails in line with the evidence that negative returns are typically much more dependent than positive returns (Das and Uppal, 2004; Patton, 2004; Garcia and Tsafack, 2008).

The attention we pay to tail dependence—rather than to the usual beta measures—is well in line with the growing interest in tail risk (see, among others, Longin and Solnik, 2001; Ang, Chen, and Xing, 2006; Patton, 2006). Tail risk is particularly relevant to hedge funds for the nonlinear nature of their payoffs is such that returns could well exhibit strong tail correlation with more traditional asset classes, breaking down any diversification gain in periods of financial distress.

This paper proposes a semiparametric framework to assess dynamic nonlinear risks in the hedge fund industry using daily data from September 2004 to May 2008. We characterize the dependence structure between asset returns using a copula approach. This is very convenient because it allows us to model the joint distribution of asset returns in two steps. We first fit models for the individual return series and then combine them into a coherent multivariate distribution by means of the copula function. Given the empirical evidence of
asymmetric co-dependence between asset returns, we deal with nonlinear risks by focusing on lower-tail dependence by means of two particular copula functions, namely, the Clayton and rotated Gumbel copulae. The choice of these two copula specifications finds empirical support in the data. Also, we let the copula parameter governing the lower-tail dependence structure between hedge funds and broad-market returns vary over time according to the degree of market uncertainty. To proxy for the latter, we employ a single index that pools the information given by the term spread, the VIX index, and the volatility risk premium. We include the term spread for it contains information about the future real economic activity (see, among others, Harvey, 1988; Estrella and Hardouvelis, 1991) as well as about future investment opportunities (Petkova, 2006). Whaley (2000) argues that the VIX index is a barometer to the market’s perception of risk and, accordingly, partially determines the amount of liquidity available in the market. Finally, the volatility risk premium relates to investors’ risk aversion (Bollerslev, Gibson, and Zhou, 2008), on top of providing a link with macroeconomic uncertainty (Bollerslev, Gibson, and Zhou, 2008; Corradi, Distaso, and Mele, 2008; Drechsler and Yaron, 2008). It is also of particularly relevance here given that hedge funds normally have significant exposure to variance risk (Bondarenko, 2004).

In this respect, our approach is closest in spirit to those of Billio, Getmansky, and Pelizzon (2007) and Adrian and Brunnermeier (2009) in that we evaluate the degree of co-dependence conditional on the state of the market. The focus of our investigation is, however, different from theirs. While we aim to highlight how hedge funds vary their tail risk exposures over time according to market uncertainty, Billio, Getmansky, and Pelizzon (2007) restricts attention to time-varying linear measures of risk by assuming a factor structure in which loadings depend on Markov-switching volatility regimes. As per Adrian and Brunnermeier (2009), they estimate conditional tail correlations using quantile regressions so as to study risk spillovers among financial institutions and, in particular, the role that hedge funds play in systemic crises. Despite of the different goal of their analysis, Adrian and Brunnermeier take a similar avenue to ours by positing that tail correlations depend on the short-term interest rate, the credit spread, the liquidity spread, the term spread, and the VIX index. The problem of restricting attention to tail correlations is that they are a function of the dependence structure as well as of the marginal distributions. This is obviously a shortcoming for it does not allow one to individuate whether the time-varying
nature of conditional tail correlations is due to variations in the dependence structure or in the conditional marginals. In contrast, we focus on conditional tail dependence, whose invariance to changes in the marginal distributions makes it much easier to interpret.

Our main empirical findings are as follows. Our preliminary descriptive analysis reveals that most hedge-fund style indices entail expected returns at par with equity and bond returns, though with much lower volatility. All hedge fund returns exhibit substantial negative skewness and excess kurtosis. The market-neutral style index is the least asymmetric, though by far the most leptokurtic. Serial correlation is also typically much larger for hedge-fund returns than for any broad-market return, in line with price smoothing and liquidity effects (Getmansky, Lo, and Makarov, 2004). We also evince significant unconditional correlation between returns on the S&P500 index and on some equity-based styles (e.g., equity hedge, event driven, and market directional). The correlation between hedge-fund returns and commodity index returns is at most moderate, with the highest values at around 0.30. In contrast, the correlations with bond and currency markets are typically negative, up to -0.29. As for tail risk, we uncover strong lower-tail dependence among styles and, to a lesser extent, with the S&P500 index. There are only three hedge-fund styles that feature neither correlation nor lower-tail dependence with any other style or asset class, namely, convertible arbitrage, distresses securities, and equity market neutral.

We then ask whether the picture remains the same if we condition tail dependence with equity returns upon market uncertainty. We find that the overall panorama actually changes drastically, illustrating well the pitfalls of restricting attention to unconditional measures. The only hedge fund style indices for which we cannot really reject tail neutrality, regardless of whether conditional or unconditional, are the convertible arbitrage and equity market neutral styles. All other hedge fund styles feature time-varying conditional tail equity risk driven by market uncertainty even if they exhibit little unconditional lower-tail dependence. In particular, the lower-tail dependence between most hedge fund styles and the S&P500 index typically decreases with market uncertainty, ensuring some diversification gains even within periods of falling stock markets.

The merger arbitrage and relative value arbitrage style indices are the exceptions, with tail equity risk exposure increasing with market uncertainty. This is not surprising given

\[2\] Fernandes, Medeiros, and Saffi (2008) unveil similar evidence for linear measures of dependence in the hedge fund industry by letting both alpha and betas to depend on market uncertainty.
that these styles normally employ spread trading strategies, often translating into low volatility bets. On the one hand, market uncertainty typically increases in periods of falling equity markets. On the other hand, spread trading usually entails negative returns when volatility is high. Altogether, this means that the likelihood of a joint lower tail event increases as well, thus explaining why we find that their tail equity risk exposure increases.

Despite of their relative importance in the hedge fund sector, the increasing tail risk exposure of the merger arbitrage and relative value arbitrage styles do not seem to compromise the overall trend in the industry. Every broad index, including the absolute return index, seems to exhibit lower-tail dependence with equity markets that chills out with market uncertainty. This puts in check the fear that hedge funds might play a major role in episodes of financial contagion.

The outcome is very different for other traditional asset classes. First, the hedge fund industry does not seem to have, on average, any tail risk exposure to bond and currency markets. Second, the only style for which we find some evidence of significant lower-tail dependence with commodity markets is the macro style. In particular, the tail risk exposure of macro hedge funds to commodity prices increases with market uncertainty. This is somewhat consistent with Edwards and Caglayan’s (2001) evidence that commodity trading advisors as well as hedge funds within the macro style normally entail higher returns in bear stock markets, thereof providing substantial protection to downside risk in the equity markets.

Our findings are very robust to variations in the copula specification. In particular, the quantitative results are very similar regardless of whether we employ the Clayton or rotated Gumbel copulae to model lower-tail dependence. Proxying market uncertainty with options-implied variance and variance risk premium (rather than their volatility counterparts) produces similar results, as well. If one includes both volatility and variance in a polynomial-type specification for the tail dependence parameter, then only the volatility terms remain significant. In addition, incorporating credit spread into the single index that determines the time-varying nature of the tail parameter yields insignificant coefficients that do not affect qualitatively the outcome. At first glance, this seems at odds with Billio, Getmansky, and Pelizzon (2007), who evince a negative exposure of hedge funds to credit

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Footnote: According to the HFR reports, historically, these styles would together manage about 15% of the assets in the industry (or circa 11% if including funds of funds). Their relative significance is difficult to pin down, though, as it also depends on leverage ratios.
risk in periods of high volatility. However, conditional beta exposure to credit risk does not necessarily imply a conditional lower-tail dependence. Finally, we show that our model not only fits very well the lower tails but also entails coefficient estimates that are reassuringly stable over time.

This is the first study to tackle conditional tail dependence in the hedge fund sector using a semiparametric copula approach. As for unconditional tail dependence, there are a few papers in the literature. Geman and Kharoubi (2003) find significant lower-tail dependence between returns on hedge-fund, mutual-fund, bond- and equity-market indices. In line with our results, the market-neutral style proves an exception in that it is the only to satisfy tail neutrality. Bacmann and Gawron (2004) evince similar results and, in addition, document substantial lower-tail dependence among the different hedge-fund styles. Their findings are quite sensitive to the sample period, though. In particular, tail dependence becomes insignificant if one excludes the Russian crisis in August 1998 from the sample. Bacmann and Gawron interpret the sensitivity with respect to the Russian crisis as evidence supporting a link between tail dependence and market liquidity. This is in line with our evidence of time-varying tail risk driven by market uncertainty given that the amount of liquidity in the market decreases with uncertainty. Brown and Spitzer (2006) carry out a similar tail risk analysis using style portfolios of individual hedge funds. They show that style portfolios display significant lower-tail dependence with equity markets even if one eliminates periods of financial distress such as, e.g., the LTCM episode. This is in contrast with Patton (2007), who fails to reject tail neutrality for most individual hedge-fund returns. A possible explanation for these conflicting results reside in the fact that tests based on individual hedge-fund data are presumably less powerful due to shorter and noisier samples.

Boyson, Stahel, and Stultz (2008) take a very different avenue, focusing on a regression-based approach to model contagion between asset classes. In particular, they estimate the probability of a hedge-fund style index to display a performance at the lower 10% tail as a function of the number of other hedge-fund styles with similar poor performances. They find strong contagion across style index returns, especially in times of low market liquidity. They also report mixed evidence of contagion running from hedge funds to more traditional asset classes. Poor performance in the hedge fund sector does not seem to affect much
the probability of a poor performance in the bond and equity markets, though there is a substantial impact in currency markets probably due to the unwinding of carry trades.

The remainder of this paper ensues as follows. Section 2 describes the copula approach we employ to model tail dependence as a function of market uncertainty. This is our primary methodological contribution to the literature in that, by modeling tail dependence conditional on market uncertainty, we are able to track how tail risk evolves over time in the hedge fund sector (even if the unconditional tail dependence is close to zero). Section 3 describes the main features of hedge-fund style index data, paying special attention to how they seem to co-move with more traditional asset classes. Section 4 reports the main results concerning the conditional lower-tail dependence between hedge funds and more traditional asset markets. It turns out that there are indeed hedge fund styles that feature very little unconditional, but relatively high conditional tail dependence with equity markets in periods of pronounced market uncertainty. Section 5 concludes by offering some final remarks.

2 Conditional copula and tail dependence


Our set-up is the following. Let $X_t$ and $Y_t$ denote continuous asset returns with conditional distributions $F_{t}^{(X)}$ and $F_{t}^{(Y)}$ given the information set spanned by $Z_t \equiv \left[ \mathbf{W}_t, X_{t-1}, Y_{t-1}, X_{t-1}, Y_{t-1}, \ldots, X_{t-k}, Y_{t-j}, \mathbf{W}_{t-k} \right]^T$, which as usual contains past information on $Y_t$, $X_t$ and some exogenous risk factors $\mathbf{W}_t$ affecting asset returns. In what follows, we make use of Patton’s (2006) extension of the
Sklar’s theorem to a conditional setting (see Appendix A for details). He shows that one may decompose the conditional joint distribution of \((X_t, Y_t)\) into

\[
F_t^{(X,Y)} = C_t \left( F_t^{(X)}, F_t^{(Y)} \right),
\]

where \(C_t\) is the unique conditional copula function. The latter is a bivariate distribution function with uniform marginals over the unit interval, that forms the conditional joint distribution by coupling the conditional univariate distributions. It essentially captures the dependence structure between \(X_t\) and \(Y_t\) given \(Z_t\).

Assuming the twice-differentiability of the conditional joint distribution and of the conditional copula function as well as the differentiability of the conditional marginal distributions yields the equivalent decomposition for the conditional joint density function:

\[
f^{(X,Y)}(x, y \mid z_t) = f^{(X)}(x \mid z_t) f^{(Y)}(y \mid z_t) c(u_X, u_Y \mid z_t),
\]

where \(u_X \equiv F^{(X)}(x \mid z_t)\) and \(u_Y \equiv F^{(Y)}(y \mid z_t)\). Equation (2) is readily available for empirical work. Taking logs of both sides of (2), it follows that the conditional joint log-likelihood function is equal to the sum of the conditional marginal log-likelihoods and the conditional copula log-likelihood. Further, assuming that the parameters in the copula and marginal densities are variation free, it follows from (2) that one may separate the maximization of the joint likelihood into two steps. We first estimate the marginals that provide the best fit to the univariate return series, and then model the dependence structure by virtue of the copula function.

### 2.1 Marginal distributions

The generalization of Sklar’s theorem to conditional distributions requires one to employ the same information set for the marginal distributions and for the copula function. Otherwise, the resulting left-hand side of (1) typically does not satisfy the conditions to be a proper conditional joint distribution function. This means that, in principle, we should specify the conditional mean and variance of the marginal distributions as a function of the same factors that affect the copula density.\(^4\) Attempting to do so however yields too many parameters because the illiquidity and price smoothing that characterize hedge fund returns would lead

\(^4\) Alternatively, one could also employ the more general notion of conditional pseudo-copula density put forth by Fermanian and Wegkamp (2004) for which it is not necessary to condition each marginal distribution on the same information set.
to factors appearing not only contemporaneously but also at different lags (Getmansky, Lo, and Makarov, 2004). In addition, some preliminary regression results show that the factors driving tail dependence do not significantly affect the first two conditional moments of the marginal distributions.

We thus model the first two conditional moments of returns using individual MA(10)-GARCH(1,1) processes:

\[
\begin{align*}
    r_{i,t} &= \mu_i + e_{i,t} + \sum_{j=1}^{10} \zeta_{i,j} e_{i,t-j}, \quad \text{with } e_{i,t} = h_{i,t} \xi_{i,t} \\
    h_{i,t}^2 &= \omega_i + \alpha_i e_{i,t-1}^2 + \beta_i h_{i,t-1}^2,
\end{align*}
\]

where \( \xi_{i,t} \) is a white noise with mean zero and unit variance for \( i \in \{X, Y\} \). The moving average specification is convenient for it typically controls reasonably well for illiquidity and performance smoothing in hedge fund returns (Getmansky, 2004; Getmansky, Lo, and Makarov, 2004; Patton, 2007).

We make no distributional assumptions on \( \xi_{i,t} \), and therefore estimate the parameters in (3) and (4) using quasi-maximum likelihood (QML) methods. We then transform the standardized residuals into uniform variates through the empirical cumulative distribution function (see Appendix B for more details).

2.2 Tail dependence structure

Having modeled the univariate return distributions, we now turn our attention to specifying a co-dependence structure between them. Chen and Fan (2006a) show that, even under copula misspecification, it is possible to estimate a particular form of dependence. This mitigates the consequences of choosing the “wrong” functional form for the copula function. For instance, if the interest lies exclusively on tail risk, it suffices to specify a copula function that captures well lower-tail dependence rather than the whole dependence structure. We thus restrict attention to the rotated Gumbel and Clayton copulae for they characterize lower-tail dependence by means of a single parameter. As expected, the rotated Gumbel and Clayton models entail very similar findings regarding the degree of lower-tail dependence.

Assuming a time-varying parameter for the rotated Gumbel specification yields the

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5In particular, they show that the QML estimator of the copula dependence parameter converges to the pseudo-true value that minimizes the Kullback-Leibler information criterion between the candidate and true copula density functions.
following copula function:
\[ C_G^G(u, v) = u + v - 1 + \exp \left\{ - \left( \left[ - \log(1 - u) \right]^{\theta_G} + \left[ - \log(1 - v) \right]^{\theta_G} \right)^{1/\theta_G} \right\}, \] (5)

with \( \theta_G^G \equiv \theta_G^G(z_t) > 1 \). The rotated Gumbel implies asymmetric dependence in that there is no upper-tail dependence, whereas the coefficient of lower-tail dependence increases with the copula parameter, viz.,
\[ \lambda_G^G \equiv \lim_{u \to 0} \frac{C_G^G(u, u | z_t)}{u} = 2 - 2^{1/\theta_G^G}. \]

The Clayton copula entails a similar asymmetry in the dependence structure in that
\[ C_C^C(u, v) = \left[ u^{-\theta_C} + v^{-\theta_C} - 1 \right]^{-1/\theta_C} \] (6)
features no dependence in the upper tail, while displaying lower-tail dependence given by
\[ \lambda_C^C = 2^{-1/\theta_C^C} \text{ with } \theta_C^C \equiv \theta_C^C(z_t) > 0. \]

It now remains to specify how the conditional lower-tail dependence parameter evolves over time. We assume that \( \lambda_{t|t-1} \) is a function of market uncertainty, which we proxy using a single index that combines the term spread, the VIX index, and the volatility risk premium. The term spread stands for a leading indicator of recessions (Harvey, 1988; Estrella and Hardouvelis, 1991; Estrella and Mishkin, 1998; Adrian and Estrella, 2008) and thus reflects the uncertainty in the real economy. In addition, Petkova (2006) shows that term spread innovations also help describe future investment opportunities. The VIX index is a model-free measure of the options-implied volatility of the S&P500 index. As such, it essentially provides ex-ante risk-neutral expectations of the future volatilities, acting as a barometer to the overall market sentiment (Whaley, 2000). See Jiang and Tian (2005) for the information context of the VIX index as a predictor of future realized volatility.

The volatility risk premium (VOLPREMIUM) not only relates to the coefficient of relative risk aversion but also co-moves with several macroeconomic variables, reflecting a pronounced counter-cyclical dynamics (Bollerslev, Gibson, and Zhou, 2008; Corradi, Distasio, and Mele, 2008). Drechsler and Yaron (2008) indeed establish a link between variance risk premium and macroeconomic uncertainty within a long-run risk model. Apart from matching the main features of asset returns, their calibration exercise is able to reproduce a level of return predictability for the variance risk premium similar to the one we observe in the data. In addition, within Bollerslev, Tauchen, and Zhou’s (2008) stylized general equilibrium model, the variance risk premium not only explains a significant portion of aggregate
stock market returns (with high premia predicting low future returns and vice-versa), but also entails more predictive power than the usual suspects such as the price-dividend ratio, default spread, and consumption-wealth ratio. Finally, volatility premia are particularly relevant for hedge funds given that they typically feature substantial exposure to variance risk (Bondarenko, 2004).

We propose to model the time-varying nature of the lower-tail dependence by

$$\lambda_t \equiv \lambda(z_t) = \Lambda(\theta_0 + \theta_1 \text{VIX}_{t-1} + \theta_2 \text{VOLPREMIUM}_{t-1} + \theta_3 \text{TERMSPREAD}_{t-1})$$

(7)

where the logistic function $\Lambda(\cdot)$ ensures that the lower-tail dependence coefficient lies in the unit interval, i.e., $0 < \lambda_t < 1$. This is equivalent to assuming that

$$\theta^G_t = \frac{\log 2}{\log \left[ 2 - \Lambda(\theta_0 + \theta_1 \text{VIX}_{t-1} + \theta_2 \text{VOLPREMIUM}_{t-1} + \theta_3 \text{TERMSPREAD}_{t-1}) \right]}$$

for the rotated Gumbel copula in (5) and that

$$\theta_t = -\frac{\log 2}{\log \Lambda(\theta_0 + \theta_1 \text{VIX}_{t-1} + \theta_2 \text{VOLPREMIUM}_{t-1} + \theta_3 \text{TERMSPREAD}_{t-1})}$$

for the Clayton specification in (6).

We estimate the copula parameters $\theta = (\theta_0, \theta_1, \theta_2, \theta_3)$ by QML method. It turns out that the estimation of the MA-GARCH model does not affect the asymptotic distribution of the QML estimator of the copula parameters. Unfortunately, the same does not apply to the estimation of the marginal cumulative distribution function by means of the empirical distribution. See discussion in Chen and Fan (2006a,b). To circumvent this issue, we compute asymptotically valid standard errors by bootstrapping the standardized residuals. See Appendix B for more details about the bootstrap procedure.

To check how well our semiparametric copula models fit the data, we follow a testing strategy that is very similar to Christoffersen’s (1998) procedure to assess forecast interval accuracy. We examine the empirical coverage of the semiparametric copula models we estimate in their joint lower tails. In particular, we focus on the event that both returns are inferior to either the first decile or first quartile of the joint distribution. Our exclusive attention to the joint lower tail is in contrast with Patton (2006), who consider several regions of the support of the joint distribution. We do not pay much attention to other regions of the support because of the semiparametric nature of our copula specification. The interest is not in modeling the whole joint distribution of traditional asset classes and hedge fund styles, but exclusively the lower-tail dependence among them.
3 Data description

Our data set concerning the hedge-fund industry consists of the daily HFRX indices from Hedge Fund Research, Inc. The single-strategy HFRX indices are convertible arbitrage (CA), distressed securities (DS), equity hedge (EH), equity market neutral (EMN), event driven (ED), macro (M), merger arbitrage (MA), and relative value arbitrage (RVA). To also represent the broad population of hedge funds, we employ the following HFRX indices: global (GL), equal weighted strategies (EW), absolute return (AR), and market directional (MD). The GL index aggregates the above strategies into a single index by virtue of an asset-weighted average based on the distribution of assets in the hedge fund industry, whereas every strategy receives equal weight in the EW index. The AR and MD indices are asset-weighted as the GL index, but they further select constituents that are likely to entail a performance not very sensitive to market conditions and to add value by betting on the direction of various financial markets, respectively. See http://www.hedgefundresearch.com for more details.

We employ the S&P500 index to measure the movements in equity markets, the Lehman global bond index (LGBI) for bond markets, the Goldman Sachs commodity index (GSCI) for commodity markets, and the US dollar index (USDX) for currency markets. The latter gauges the trade-weighted value of the US dollar relative to the six major world currencies: the euro, Japanese yen, Canadian dollar, British pound, Swedish krona, and Swiss franc. To proxy for market uncertainty, we consider the term spread, as measured by the difference between the yields of the 30-year and 3-month US treasuries, as well as the VIX index and the volatility risk premium. The VIX index is the options-implied volatility of the S&P500 index from the Chicago Board Options Exchange, whereas we gauge the volatility risk premium by the difference between the realized and implied volatilities of the S&P500 index. We compute the realized volatility using 5-minute returns on the S&P500 futures index.

Our sample runs from September 2004 to May 2008, yielding a total of 926 daily observations. Table 1 reveals that bond and equity returns (with continuous compounding) are on average about 2.5%, even though volatility is twofold for the S&P500 index. The negative average change in the USDX index reflects the weakening of the US dollar as much as the very high average GSCI return mirrors the very recent commodity boom.
In addition, the standard deviation of the latter also illustrates the traditional view that commodity prices are among the most volatile of international prices (Kroner, Kneafsey, and Claessens, 1995; Pyndyk, 2004; Blattman, Hwang, and Williamson, 2007). As for higher-order moments, only the S&P500 index exhibits substantial excess kurtosis, whereas skewness is material for both equity and bond markets. In particular, skewness is negative for the S&P500 index and positive for the Lehman global bond index. The former emulates the well-known leverage effect, while the latter is typical of bonds with low default risk. Finally, stock market returns and squared returns displays significantly more autocorrelation than their counterparts in the bond, commodity and currency markets.

In line with the stylized facts of the hedge-fund literature, we find that most styles entail average returns that are comparable with equity and bond expected returns, though with much lower volatility. In addition, all hedge fund returns exhibit substantial negative skewness and excess kurtosis, confirming the literature’s concern with fat tail risk. It is interesting to observe that equity market neutral is the least asymmetric, while by far the most leptokurtic. As expected, autocorrelation is also much stronger for hedge-fund returns than for any broad-market return due to performance smoothing and to illiquidity exposure (Getmansky, Lo, and Makarov, 2004). With exception perhaps to the distressed securities style index, squared returns are also very persistent in the hedge fund sector. Altogether, these results warrant the MA-GARCH specification for hedge-fund returns.

We next turn to the co-movements between hedge-fund returns and broad-market returns. Table 2 unveils significant unconditional correlation between the S&P500 index and some of the equity-based styles (e.g., equity hedge and event driven). Correlation with the commodity index is always positive, with highest values corresponding to the macro style (about 0.36) and to the overall industry (around 0.30 for the GL, EW, AR, and MD indices). In contrast, correlations with bond and currency markets are typically negative, ranging from 0.11 to -0.29. Finally, there is also significant positive correlation among hedge-fund styles as in Boyson, Stahel, and Stultz (2008).

Table 3 complements the above results by running Poon, Rockinger, and Tawn’s (2004) test of tail dependence. There is strong (unconditional) lower-tail dependence among styles and, to a lesser extent, with the S&P500 index. Convertible arbitrage, distressed securities, and equity market neutral are the only styles featuring neither correlation nor lower-tail
dependence with any other style or asset class. As for upper-tail dependence, it appears significant only among hedge-fund styles. There is significant upper-tail dependence with the S&P500 index only for very few styles, while we find none with bond, commodity, and foreign exchange markets. This not only conforms with previous results in the literature on asymmetric dependence, but also provides some reassuring evidence as to what concerns our decision to focus exclusively on lower-tail dependence.

4 Conditional tail risk in the hedge fund industry

Our empirical analysis is in two steps. We first filter the different index returns by means of univariate MA-GARCH models, and then investigate whether market uncertainty drives the lower-tail dependence among their standardized residuals using either Clayton or rotated Gumbel copula functions. In contrast to Boyson, Stahel, and Stultz (2008), we focus on the conditional lower-tail dependence between hedge fund styles and broad-market returns, paying no attention whatsoever to tail dependence within the hedge fund sector.

4.1 Filtering index returns

To allow for performance smoothing over the month, we start with a MA(22) structure for the hedge fund styles and then eliminate insignificant MA coefficients using a standard general-to-specific model selection procedure. The resulting MA structures are as follows: no lags for the LGBI, GSCI and USDX returns and for the MA style; lag one for the S&P 500 index and for the EH and ED styles; lags 1 and 10 for the MD and M styles; lags 1, 2 and 10 for the GL and EW indices, lags 1, 2, 3 and 10 for the AR index, lags 1, 5 and 8 for the EMN style; lags 1, 3, 10, 12, 15 and 22 for the CA style; lags 1, 2, 3, 5, 7, 8, 10, 12, 15, 19 and 20 for the DS style; and lags 2, 4, 5, 10, 11, 12, 14, 20 and 21 for the RVA style. It is worth mentioning that filtering hedge fund returns by means of a full MA(22) specification does not change the qualitative results we uncover in the next subsection for the joint distribution between broad-market returns and hedge fund styles.

Table 4 reports the QML estimates for the univariate MA-GARCH(1,1) models. The first striking feature concerns the length of the MA structure for the different index returns. While the only broad-market return to require a MA structure is the S&P500 index and of first order, most hedge-fund styles exhibit a much more persistent behavior, calling for a richer MA structure. It is not surprising that the serial correlation (as measured by
the sum of the MA coefficients) is relatively stronger for hedge-fund returns. Getmansky, Lo, and Makarov (2004) indeed show that hedge fund typically display higher levels of autocorrelation due to the combination of illiquidity exposure and performance smoothing.

The smoothing index is lowest for the DS style at 0.330, reflecting the fact that distressed securities are typically less liquid. In addition, it is also substantially different from one for every industry index as well as for the macro and relative-value-arbitrage styles, suggesting some exposure to liquidity risk (e.g., probably due to investments in emerging markets) and/or performance smoothing. In contrast, we find very little evidence of smoothing within the equity-market-neutral and merger-arbitrage styles. These findings complement well Getmansky, Lo, and Makarov’s (2004) smoothing analysis using hedge-fund style indices from the TASS database.  

As for the conditional variance, we observe that hedge-fund and broad-market returns exhibit very persistent behavior in the second moment, though still satisfying geometric ergodicity ($\hat{\alpha} + \hat{\beta} \approx 1$, with $0.026 \leq \hat{\alpha} \leq 0.213$ and $0.749 \leq \hat{\beta} \leq 0.970$). As we fail to find any evidence of residual heteroskedasticity at the 5% level of significance, we conclude that the GARCH(1,1) specification suffices to describe the time-varying volatility of the different index returns.

Table 5 reports the results of Poon, Rockinger, and Tawn’s (2004) test of unconditional tail dependence between pairs of MA-GARCH standardized residuals. We find even less evidence of unconditional tail dependence after controlling for serial correlation and conditional heteroskedasticity. For instance, macro and merger arbitrage joins convertible arbitrage, distressed securities, and equity market neutral among the styles displaying no unconditional tail dependence with any other style or asset class. As before, most of the tail dependence is among styles, especially with respect to the broad hedge-fund indices (i.e., GL, EW, AR, and MD), rather than across asset classes. As for the traditional asset classes, we evince only a few hedge fund styles exhibiting tail risk exposure, and exclusively to equity markets. In particular, we fail to reject the null of unconditional lower-tail dependence with the S&P500 index at the 5% significance level only for the relative-value-arbitrate style and for the equal-weighted index. At the 1% significance level, we start failing to reject lower-tail dependence also for the asset-weighted global index and for the equity-hedge and macro styles.

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It remains to investigate whether conditioning on market uncertainty changes or not the lower-tail dependence structure between hedge-fund styles and broad-market returns. This is precisely the goal of the next section.

4.2 Joint distributions

For every pair of hedge fund style/index and broad-market standardized residuals, we estimate both Clayton and rotated Gumbel copula functions, with time-varying parameters driven by market uncertainty. Note that we do not attempt to model tail dependence among styles for the focus is on diversification gains with respect to traditional asset classes.

Table 6 reports the results for the hedge fund styles with conditional lower-tail dependence driven by market uncertainty. It is striking how the picture changes dramatically once we condition on market uncertainty in that most hedge fund styles now seem to exhibit dynamic exposure at least to equity tail risk. In particular, lower-tail dependence with the S&P500 index decreases in a significant manner with market uncertainty in the hedge fund industry, mitigating the likelihood of a diversification break down within periods of falling stock markets. That in the overall the hedge fund industry seem to reduce their tail risk exposure in times of uncertainty also casts a doubt on the fear that hedge funds might play a major role in episodes of financial contagion (Chan, Getmansky, Haas, and Lo, 2006).

Despite of the little evidence of unconditional tail dependence, the distressed securities style displays conditional exposure to equity tail risk that declines dramatically with the VIX index. We also observe tail dependence decreasing with market uncertainty for the equity hedge, event driven, and macro styles. In contrast, lower tail dependence of the merger arbitrage style with the S&P500 index upping with the term premium and with the volatility risk premium, but decreases with the VIX index. The overall effect is a tail risk exposure to the S&P 500 index that increases with market uncertainty. The relative value arbitrage style displays a similar pattern, with lower tail dependence rising with the VIX index.

Figure 1 plots how the conditional tail dependence with the S&P500 index evolves for hedge-fund returns over time. In the first row, we observe that the AR and MD aggregate indices behave in a very different manner. Tail risk exposure of hedge funds that engage in directional bets depend both on the VIX index and on the volatility risk premium as well.
as on the term premium. In contrast, the conditional tail dependence of the AR index does not depend on equity volatility, being a function exclusively of the term premium. As for the overall aggregate indices, tail risk is more volatile for the equal-weighted index than for the global index, reflecting the former’s dependence on the volatility risk premium. Despite the different specifications, the story is the same for all aggregate hedge-fund indices in that tail dependence diminishes with market uncertainty.

The second and third rows in Figure 1 reveal a mixed pattern. Four out of the six styles for which there is evidence of conditional tail dependence behave similarly to the aggregate hedge-fund indices in that tail risk exposure decreases with market uncertainty.
In particular, the plots for the distressed securities and macro styles are similar to that of the absolute return index, whereas those for the equity hedge and event driven styles resemble more the behavior of the market directional index. This reflects not only the effort that hedge funds within DS and M styles put to entail performances that are not very sensitive to equity market conditions (as here represented by equity volatility), but also the fact that the EH and ED styles normally do directional bets. On the other hand, at odds with what happens in the overall industry, the conditional tail dependence with the S&P500 index increases with market uncertainty for the merger arbitrage and relative value arbitrage styles. It is actually not very surprising that the latter styles are exceptions to the rule given that their spread trading is more likely to entail negative returns in periods of high volatility and illiquidity, i.e., greater market uncertainty. Given the negative correlation between the S&P500 index returns and its volatility, the MA and RVA tail equity risk exposures are bound to escalate with market uncertainty.

The picture is very different for the other broad-market returns. Given their slightly negative correlations with hedge fund returns, it is not surprising that we find neither conditional nor unconditional tail risk exposure to bond and currency markets. The evidence is a bit more mixed as to what concerns lower-tail dependence with commodity markets. Apart from some very weak evidence of time-varying lower-tail dependence for the hedge-fund sector as a whole, our analysis reveals that the tail risk exposure of macro hedge funds to commodity prices increases with market uncertainty. This is consistent with Edwards and Caglayan’s (2001) evidence that commodity trading advisors as well as hedge funds within the macro style normally entail higher returns in bear stock markets, thereof providing substantial protection to downside risk in the equity markets.

We are very confident in our results for three reasons. First, although we only report in Table 6 the results for the best fitting copula, there is no qualitative change if one replaces the Clayton copula with the rotated Gumbel or vice-versa, in that the coefficient estimates are always of the same sign and magnitude. In addition, the hit test à la Christoffersen (1998) that we perform to assess the empirical coverage in the joint lower tails indicate that the Clayton and rotated Gumbel copula functions are flexible enough to capture well the corresponding dependence structure. Second, a recursive analysis show that the QML estimates of the copula coefficients are very stable over time, ensuring that our findings are
Figure 2: Recursive quasi-maximum likelihood estimates of the conditional rotated Gumbel copula parameters for the S&P500 index and HFRX global index, with their 95% bootstrap-based confidence interval.

not spurious due to overfitting or copula misspecification. Figure 2 illustrates this stability by plotting the recursive QML estimates of the copula coefficients for the aggregate global index.

We check how robust our empirical findings are to different specifications for the copula model. First, replacing the VIX index and the volatility risk premium with their variance-based counterparts does not have a qualitative impact in the results. Second, assuming a polynomial-type specification including both volatility and variance terms does not pay off either in that only the volatility-based measures of market uncertainty remain significant. Third, incorporating credit spread into the single index that determines the time-varying
nature of the tail parameter yields insignificant coefficients and hence does not affect qualita-
tively the outcome. This is a bit surprising, though not inconsistent with Billio, Getmansky,
and Pelizzon’s (2007) evidence that hedge funds typically have a negative exposure to credit
risk in periods of high volatility for a nonzero conditional beta does not necessarily translate
into lower-tail dependence.

Finally, the only hedge fund styles for which we fail to reject tail neutrality, regardless of
whether conditional or unconditional, are convertible arbitrage and equity market neutral.
In the next section, we explore their tail neutrality to a deeper extent by breaking down
equity returns into market segments based on value, growth and market capitalization.

4.3 Tail neutrality

So far, we proxy equity broad-market returns by means of the S&P500 index returns. In
this section, we replace the S&P500 index with the family of Russell stock market indices
so as to test whether tail neutrality indeed holds for the convertible arbitrage and equity
market neutral styles once we control for stock characteristics. In particular, we estimate
our semiparametric copula models of lower-tail dependence for the Russell indices and their
value and growth sub-indices.

The Russell 3000 broad-market index measures the performance of the largest 3,000
US firms representing about 98% of the investable US equity market, whereas the Russell
top 200 index considers only the largest 200 US firms (about 65% of the total market
capitalization). The Russell midcap index reflects the performance of the mid-cap segment
of the US equity universe by looking approximately at the smallest 800 smallest firms within
the largest 1,000 firms in the US market. The Russell 2000 index includes approximately
2,000 of the smallest securities based on a combination of their market capitalization and
current index membership (about 8% of the US market). Finally, the Russell microcap
index assesses the performance of the microcap segment (less than 3% of the total market
capitalization) by including 1,000 of the smallest securities in the small-cap Russell 2000
index. The corresponding growth and value sub-indices also rank firms according to their
price-to-book ratios and forecasted growth values.

Table 7 reports the results for the equity market neutral style only given that we find no
evidence of time-varying lower tail dependence for the convertible arbitrage style regardless
of the Russell index we use. Tail risk exposure to the Russell indices does not vary with
the volatility-based measures, though it seems to decrease with the term premium (at least at the 10% level of significance). The strength of this dependence is almost identical across indices, implying a lack of sensitivity to the book-to-market value. As for market capitalization, the intercepts are also about the same across the board apart from the Russell midcap indices. Although the latter estimates are slightly less negative, the resulting time series of lower-tail dependence are at par with the ones for the other Russell indices (see plots in Figure 3). All in all, although we are able to identify time-varying coefficients for the lower-tail dependence between the equity market neutral style and the Russell indices that are driven by the term premium, it is hard to imagine that they are indeed economically significant given their small magnitude (and large confidence interval).
5 Conclusion

This paper asks whether market uncertainty drives tail risk exposure in the hedge fund industry. Although Ribeiro and Veronesi’s (2002) rational expectations model posits that cross-correlations among different markets should increase in bad times, it is not necessarily the case that tail dependence should vary as well. The latter is actually invariant to changes in the conditional marginal distributions and hence conditional heteroskedasticity does not play a role. We nonetheless find that most hedge fund styles feature time-varying tail risk exposure to the S&P500 index driven by market uncertainty even if they exhibit little unconditional lower-tail dependence. In particular, the lower-tail dependence of the overall hedge-fund industry decreases with market uncertainty, ensuring some diversification gains even within periods of falling stock markets. The only exceptions are the merger arbitrage and relative value arbitrage styles for which tail risk exposure to the S&P500 index increases as market uncertainty builds up.

Also, we cannot reject market tail neutrality for two hedge-fund styles, namely, convertible arbitrage and equity market neutral. This result is robust to decomposing US equity market returns according to stock characteristics (e.g., value, growth and market cap). Book-to-market ratio does not seem to have any effect, whereas lower-tail dependence for the equity market neutral style seems slightly larger, though still very small, for indices that consider only mid-cap firms.

We find very little evidence of tail dependence of hedge funds with bond and currency markets. As for the commodity markets, we evince that the macro style index exhibits more tail risk exposure in periods of high uncertainty. This is not so surprising given that macro hedge funds presumably increase in bear markets their exposure to emerging markets, whose performance typically depends heavily on commodity prices.

All in all, our findings cast at least some doubt on the claims that the hedge fund sector heavily contributes to the systemic risk in the economy. Lower tail dependence with traditional asset classes is obviously only an indirect measure of systemic risk and, as such, it is hard to gauge the actual exposures to systemic risk. However, it provides a much better picture than the correlation and quantile analyses of Chan, Getmansky, Haas, and Lo (2006) and Adrian and Brunnermeier (2009) given that we focus exclusively on tail dependence by explicitly controlling for changes in the first and second moments of the
returns. The latter is paramount given Adrian’s (2007) evidence that the recent increase in the correlation among hedge funds is mostly due to lower volatility rather than to higher covariances.

Appendix

A Extension of Sklar’s theorem to conditional distributions

Patton’s (2006) Theorem 1: Let $F_{X,Y|Z}(\cdot, \cdot|z)$ denote the conditional joint distribution of $(X, Y)$ given $Z = z$, with conditional marginals $F_{X|Z}(\cdot|z) \equiv F_{X|Z}(\cdot, \infty|z)$ and $F_{Y|Z}(\cdot|z) \equiv F_{XY|Z}(\infty, \cdot|z)$. If $F_{X|Z}(\cdot|z)$ and $F_{Y|Z}(\cdot|z)$ are continuous in $x$ and $y$ for all $z \in Z$, where $Z$ is the support of $Z$, there then exists a unique conditional copula $C(\cdot, \cdot|z)$ such that

$$F_{X,Y|Z}(x,y|z) = C(F_{X|Z}(x|z), F_{Y|Z}(y|z)|z)$$ (A.1)

for each $z \in Z$ and every $(x,y) \in \mathbb{R}^2$, with $\mathbb{R} \equiv \mathbb{R} \cup \{\pm \infty\}$. The converse is also true in that $F_{X|Z}(\cdot|z)$ as defined by (A.1) is a conditional bivariate distribution function with conditional marginal distributions $F_{X|Z}(\cdot|z)$ and $F_{Y|Z}(\cdot|z)$ given a family of conditional copulae $\{C(\cdot, \cdot|z)\}$ measurable in $z$.

B Details on the estimation strategy

It follows from (2) that the conditional joint log-likelihood function is

$$\ell(\phi_X, \phi_Y, \theta) = \sum_{t=1}^{T} \log f(X_t|z_t; \phi_X) + \sum_{t=1}^{T} \log f(Y_t|z_t; \phi_Y) + \sum_{t=1}^{T} \log c_t(\hat{u}_t, \hat{v}_t; \theta).$$ (B.2)

Under the assumption of weak exogeneity, it is possible to estimate the parameters in (B.2) in two steps. First, we estimate the marginal parameters $\phi_X$ and $\phi_Y$ by quasi-maximum likelihood and then transform the standardized residuals by means of the empirical distribution to obtain uniform variates, namely, $\hat{u}_t = \frac{1}{T+1} \sum_{\tau=1}^{T} 1(\hat{\eta}_{X,t} \leq \hat{\eta}_{X,t})$ and $\hat{v}_t = \frac{1}{T+1} \sum_{\tau=1}^{T} 1(\hat{\eta}_{Y,t} \leq \hat{\eta}_{Y,t})$ for $\hat{\eta}_{i,t} \equiv \eta_{i,t}(\hat{\phi}_i)$ with $i \in \{X, Y\}$. Second, we obtain the QML estimate $\hat{\theta}$ by maximizing with respect to $\theta$ the empirical counterpart of the third term of (B.2), i.e., $\hat{\theta} \equiv \arg\max_{\theta} \sum_{t=1}^{T} \log c_t(\hat{u}_t, \hat{v}_t; \theta)$.

It turns out that the estimation of the parameters in the conditional marginal distribution does not have an impact on the limiting distribution of the estimator of the copula parameters. Unfortunately, the same does not apply to the estimation of the resulting cumulative distribution functions by means of the empirical distribution. Put differently,
replacing \( u_t \) and \( v_t \) with their empirical counterpart is not without consequences. The estimation errors that arise while computing \( \hat{u}_t \) and \( \hat{v}_t \) affect the covariance matrix of \( \hat{\theta} \) and hence standard inference on \( \theta \) is invalid.

To solve this problem, we use a simple bootstrap procedure. In particular, we resample (with replacement) the standardized residuals \((\hat{\eta}_{i,t}, \ldots, \hat{\eta}_{i,T})\) for \( i \in \{X, Y\} \) so as to obtain \( B \) bootstrap artificial samples of the form \((\hat{\eta}^{(b)}_{i,t}, \ldots, \hat{\eta}^{(b)}_{i,T})\). We next transform these bootstrap samples using their own empirical distribution to find \((\hat{u}^{(b)}_{1}, \hat{v}^{(b)}_{1}, \ldots, \hat{u}^{(b)}_{T}, \hat{v}^{(b)}_{T})\). Finally, we estimate \( \hat{\theta}^{(b)} \) by quasi-maximum likelihood for each bootstrap replication \( b = 1, \ldots, B \).

As \( B \) grows to infinity, the sample covariance matrix of \((\hat{\theta}^{(1)}, \ldots, \hat{\theta}^{(B)})\) entails a consistent estimator for the true covariance matrix of \( \hat{\theta} \), allowing us to perform valid asymptotic inference on \( \theta \) (see, for instance, Hidalgo and Zaffaroni, 2007). Note that, as the estimation of the MA-GARCH models does not affect inference, it is not necessary to re-estimate them for each bootstrap sample.
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<th>maximum</th>
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<th>Q^2(20)</th>
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Table 1: We report some descriptive statistics for index returns on bond, commodity, currency, equity, and hedge-fund styles. The sample period ranges from September 2004 to May 2008, comprising 926 daily observations. The columns Q(20) and Q^2(20) refer to the Ljung-Box autocorrelation test up to lag 20 for returns and squared returns, respectively.
Table 2: We document the correlation matrix for daily returns on stock, bond, commodity, currency, and hedge fund indices for the sample period running from September 2004 to May 2008.
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Table 3: We employ the Poon-Rockinger-Tawn test to check for tail dependence between pairs of index returns from September 2004 to May 2008. The lower triangle refers to tests of lower-tail dependence, whereas the figures in the upper triangle relate to tests of upper-tail dependence. We report the values of the test statistic, which under the null of tail dependence must equal one, as well as their p-value within parentheses.
Table 4: We report quasi-maximum likelihood estimates, with the corresponding robust t-statistics within parentheses, for the intercept in the mean equation as well as to every parameter in the variance equation. We also summarize the information concerning the MA coefficient estimates into two statistics. The sum of the MA coefficient $\sum_{j=1}^{22} \zeta_j$ gauges the strength of the serial correlation, whereas the smoothing index $\sum_{j=0}^{22} \tilde{\zeta}_j^2$, where $\tilde{\zeta}_j = \zeta_j / \sum_{j=0}^{22} \zeta_j$ with $\zeta_0 = 1$, provides a measure of illiquidity and performance smoothing for the hedge fund returns. Finally, we also display the Ljung-Box test statistics for serial correlation in the standardized residuals and their squares ($Q$ and $Q^2$, respectively) as well as the LM test for ARCH effects ($LM^2$), with their p-values within parentheses. The sample period ranges from September 2004 to May 2008.
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Table 5: We employ the Poon-Rockinger-Tawn test to check for tail dependence between pairs of standardized residuals of the MA-GARCH filters for index returns from September 2004 to May 2008. The lower triangle refers to tests of lower-tail dependence, whereas the figures in the upper triangle relate to tests of upper-tail dependence. We report the values of the test statistic, which under the null of tail dependence must equal one, as well as their p-value within parentheses.
Table 6: We model lower-tail dependence by means of either a rotated Gumbel (rG) or a Clayton (C) copula with time-varying parameter driven by market uncertainty. We proxy the latter using a single index that combines information from the VIX index, volatility risk premium and term spread. We report QML coefficient estimates and their bootstrap-based t-statistics within parentheses. In addition, we also document under the column 'hit test' the empirical coverage of the joint lower tail for the regions given by pairs with both elements below their first quartile.
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Table 7: We model lower-tail dependence of the equity-market-neutral style index with the Russell index family by means of either a rotated Gumbel (rG) or a Clayton (C) copula with time-varying parameter driven by market uncertainty. We proxy the latter using a single index that combines information from the VIX index, volatility risk premium and term spread. We report QML coefficient estimates and their bootstrap-based t-statistics within parentheses. In addition, we also document under the column ‘hit test’ the empirical coverage of the joint lower tail for the regions given by pairs with both elements below their first quartile.