Tailing Tail Risk in the Hedge Fund Industry*

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Abstract: This paper aims to assess dynamic tail risk exposure in the hedge fund sector using daily data. We use a copula function to model both lower and upper tail dependence between hedge funds, bond, commodity, foreign exchange, and equity markets as a function of market uncertainty, and proxy the latter by means of a single index that combines the options-implied market volatility, the volatility risk premium, and the swap and term spreads. We find substantial time-variation in lower-tail dependence even for hedge-fund styles that exhibit little unconditional tail dependence. In addition, lower-tail dependence between hedge fund and equity market returns decreases significantly with market uncertainty. 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 lower-tail risk exposure of macro hedge funds to commodity markets increases with liquidity risk. Finally, further analysis shows mixed evidence on how much hedge funds contribute to systemic risk.

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

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The value of assets under management in the hedge fund industry increased from \$50 billion in 1990 to an all time high around \$1.9 trillion in October 2007. Since then, 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 Fund Weighted Composite Index, which comprises a large cross-section of hedge funds, lost around 20% of its value. Still, this is considerably lower than the 40% drop in the value of the S&P 500 Index.

The exponential growth up to 2007 was essentially due to the fact that hedge funds entail relatively high expected returns with relatively 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.

This leads to the important question of whether hedge funds offer diversification benefits. Unconditional correlation-based analysis, which captures the amount of linear association between returns, can only partially address this question. Hedge funds typically engage in 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 (e.g., Fung and Hsieh, 2001; Mitchell and Pulvino, 2001; Amin and Kat, 2003; Dor, Jagannathan, and Meier, 2003; Getmansky, Lo, and Makarov, 2004; Agarwal, Bakshi, and Huij, 2009; Diez de los Rios and Garcia, 2009).

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 returns and broad market returns is likely to rise in periods of financial distress (Edwards and Caglayan, 2001; Agarwal and Naik, 2004).[1] As a matter of fact, the correlation between the returns on HFRI Fund Weighted Composite Index and the S&P 500 monthly returns has been about twice as high in down markets (70%) than in up markets (34.5%) during the 1990-2008 period.

[1] 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 cross-market correlations increase. See also Buraschi, Porchia, and Trojani (2010) for optimal portfolio choice under time-varying stochastic correlation, as well as Buraschi, Kosowski, and Trojani (2009) for evidence of hedge funds' exposure to correlation risk.

To evaluate whether hedge funds deliver diversification benefits, there needs to be more than a simple evaluation of 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. Therefore, we examine whether *tail risk* measures the risk exposure of hedge funds during a market downturn. In this way, we assess diversification gains when markets experience large and negative returns.

Focusing on tail risk is convenient for two reasons. First, it accommodates investors' preferences concerning higher-order moments such as, for example, skewness and kurtosis (Scott and Horvath, 1980; Pratt and Zeckhauser, 1987). This is important since, as Agarwal, Bakshi, and Huij (2009) show, hedge funds have substantial exposure to higher-moment risks. The corresponding premia are indeed economically significant, playing an important role in explaining hedge fund returns. The exposures to these factors should be taken into account when evaluating hedge fund 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; Boyson, Stahel, and Stultz, 2010). Tail risk is particularly relevant to hedge funds as 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 copula-based framework to assess the dynamic nonlinear risks in the hedge fund industry. We examine daily data from September 2004 to May 2008. This is in stark contrast with most papers in the hedge fund literature, whose reliance on monthly data within a relatively larger time span reflects well their interest in performance evaluation (e.g., average returns and alphas). We consider hedge fund returns at the daily frequency because sample size matters much more than time span for estimating risk exposures (e.g., betas and tail dependence), especially if they are dynamic.[2]

We characterize the dependence structure between asset returns using a copula approach.

[2] Li and Kazemi (2007) and Boyson, Stahel, and Stultz (2010) are among the few exceptions using daily data (see the latter and Li, Markov, and Wermers, 2007, for a comparison of the data features of hedge fund returns at the daily and monthly frequencies).

This is 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 a symmetrized Joe-Clayton copula function, which models both lower and upper tail dependence. We let the copula parameters governing the 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 swap spread, the VIX index, and the volatility risk premium. We include the term spread for it contains information about the future real economic activity (e.g., Harvey, 1988; Estrella and Hardouvelis, 1991), as well as about future investment opportunities (Petkova, 2006). The swap spread, also known as TED spread, is a measure of credit risk that Brunnermeir (2009) advocates as a useful basis for gauging the severity of a liquidity crisis. 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 on top of providing a link with macroeconomic uncertainty (Corradi, Distaso, and Mele, 2008; Drechsler and Yaron, 2008; Bollerslev, Gibson, and Zhou, 2009). It is also relevant here given that hedge funds normally have significant exposure to variance risk (Bondarenko, 2004).

Our approach is similar to that in Adrian and Brunnermeier (2009) and Billio, Getmansky, and Pelizzon (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. While we aim to highlight how hedge funds vary their tail risk exposures over time according to market uncertainty, Billio, Getmansky, and Pelizzon (2009) restrict 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 the different goal of their analysis, Adrian and Brunnermeier take a similar approach 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 restriction does not allow one to uncover whether the time-varying nature of conditional tail correlations is due to variations in the dependence structure or in the conditional marginals (e.g., conditional heteroskedasticity). In contrast, we focus on conditional tail dependence, whose invariance to changes in the marginal distributions makes it much easier to interpret.

Our preliminary descriptive analysis reveals that most hedge fund style indices generate 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 find significant unconditional correlation between returns on the S&P 500 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. Finally, we find some weak evidence of upper-tail dependence only among a few hedge fund styles.

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.[3] 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 lower-tail equity risk driven by market uncertainty even if they exhibit little unconditional tail dependence. In particular, the lower-tail dependence between most hedge fund styles and the S&P500 Index typically decreases with market uncertainty, ensuring at first glance some

[3] Fernandes, Medeiros, and Saffi (2008) unveil similar evidence for linear measures of dependence in the hedge fund industry by letting both alphas and betas to depend on market uncertainty (see also Bollen and Whaley, 2009; Patton and Ramadorai, 2010).

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 that these styles normally employ spread trading strategies that often translate 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 their relative importance in the hedge fund sector,[4] 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 seems to exhibit a lower-tail dependence with equity markets that subsides with market uncertainty. This reduces the fear that hedge funds might play a major role in episodes of financial contagion (Chan, Getmansky, Haas, and Lo, 2006), and hence we carry out a simple correlation analysis to better understand systemic risk issues. Hedge funds reduce their tail exposure to equity risk in times of market uncertainty because of either uncertainty timing or forced liquidations. We should expect a positive correlation between changes in lower-tail dependence and stock market returns if the former, whereas a positive correlation between hedge fund returns and changes in tail risk if the latter, due to the heavy losses that characterize fire sales. The evidence supports only the latter, indicating that hedge funds' tail risk reduces in times of market uncertainty partly because of forced liquidations. Further analysis using a sample from June 2008 to May 2010, however, shows that, by the time the liquidity dry-up climaxes, the hedge fund industry does not have significant exposure to tail equity risk anymore.

The outcome is very different for other traditional asset classes, as well as for upper-tail dependence. First, hedge funds do 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 consistent with Edwards and Caglayan's (2001) evidence that commodity trading advisors, as well as hedge funds within the macro style, normally entail higher re-

[4] Historically, according to the HFR reports, 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.

turns in bear stock markets, thereby providing substantial protection to downside risk in the equity markets. Third, there is very little, if any, conditional upper tail dependence between hedge fund and broad market returns.

Our findings are very robust to variations in the copula specification. In particular, the quantitative results are very similar if we restrict attention to the lower tail by employing either a Clayton or a rotated Gumbel copula (see, e.g., Patton, 2004). 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 other measure of 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.

This is the first study to tackle *conditional* tail dependence in the hedge fund sector. There are a few papers, however, discussing *unconditional* tail dependence. 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 one to satisfy tail neutrality. Bacmann and Gawron (2004) find similar results and, in addition, document substantial lower-tail dependence among the different hedge fund styles; however, their findings are quite sensitive to the sample period. In particular, tail dependence becomes insignificant if one excludes the Russian crisis in August 1998 from the sample. They 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, for example, the LTCM episode. This contrasts with Patton (2009), 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 the shorter and noisier samples.

Boyson, Stahel, and Stultz (2010) 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 has little effect on the probability of a poor performance in the bond and equity markets, though there is a substantial impact in currency markets, which is probably due to the unwinding of carry trades.

The paper is organized as follows. Section 1 describes the copula approach we used 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 2 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 3 reports the main results concerning the conditional tail dependence between hedge funds and more traditional asset markets. Section 4 concludes by offering some final remarks, whereas the Appendix provides some technical details.

1 Conditional Copula and Tail Dependence

The conditional copula set-up is as follows. 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:

$$\boldsymbol{Z}_t \equiv [\boldsymbol{W}'_t, X_{t-1}, Y_{t-1}, \boldsymbol{W}'_{t-1}, \ldots, X_{t-k}, Y_{t-k}, \boldsymbol{W}'_{t-k}]',$$

which contains past information on Y_t, X_t, and some exogenous risk factors, $\boldsymbol{W}_t$, affecting asset returns. In order to isolate the estimation of the tail-dependence parameter from the estimation of the marginal distributions (Joe, 1997), we use a copula decomposition of the conditional joint distribution of hedge fund and broad market returns. To avoid an excessive number of parameters, we employ bivariate copula functions to model lower-tail dependence between each hedge fund style index with each broad market return in a pairwise fashion. This is well in line with the literature studying asymmetric dependence across markets (e.g., Ang and Chen, 2002; Ané and Kharoubi, 2003; Jondeau and Rockinger, 2003; Hong, Tu, and Zhou, 2007; Okimoto, 2008; Markwat, Kole, and van Dijk, 2009; Kang, In, Kim, and Kim, 2010).

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:

$$F_t^{(X,Y)} = C_t\left(F_t^{(X)}, F_t^{(Y)}\right), \tag{1}$$

where C_t is the unique conditional copula function. The latter is a bivariate distribution function with uniform marginals over the unit interval, which forms the conditional joint distribution by coupling the conditional univariate distributions. It essentially captures the dependence structure between X_t and Y_t given $\boldsymbol{Z}_t$.

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:

$$f^{(X,Y)}(x, y \,|\, \boldsymbol{z}_t) = f^{(X)}(x \,|\, \boldsymbol{z}_t)\, f^{(Y)}(y \,|\, \boldsymbol{z}_t)\, c(u_X, u_Y \,|\, \boldsymbol{z}_t), \tag{2}$$

where $u_X \equiv F^{(X)}(x \,|\, \boldsymbol{z}_t)$ and $u_Y \equiv F^{(Y)}(y \,|\, \boldsymbol{z}_t)$. 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.

1.1 Marginal distributions

We model the first and second conditional moments of the returns using individual MA(22)-GARCH(1,1) processes:

$$r_{i,t} = \mu_i + e_{i,t} + \sum_{j=1}^{10} \zeta_{i,j}\, e_{i,t-j}, \qquad \text{with } e_{i,t} = h_{i,t}\, \eta_{i,t} \tag{3}$$

$$h_{i,t}^2 = \omega_i + \alpha_i\, e_{i,t-1}^2 + \beta_i\, h_{i,t-1}^2, \tag{4}$$

where $\eta_{i,t}$ 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, 2009).

We make no distributional assumptions on $\eta_{i,t}$, 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).

1.2 Tail dependence structure

To characterize the conditional joint distribution, one needs to specify the dependence structure. 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 tail dependence even if ignoring the bulk of the data. We thus restrict attention to the symmetrized Joe-Clayton copula, as in Patton (2006).[5]

Assuming a time-varying parameter for the symmetrized Joe-Clayton specification yields the following copula function:

$$C_{SJC}(u, v; \theta_t^L, \theta_t^U) = \frac{1}{2}\left[C_{JC}(u, v; \theta_t^L, \theta_t^U) + C_{JC}(1-u, 1-v; \theta_t^U, \theta_t^L) + u + v - 1\right], \tag{5}$$

where the Joe-Clayton copula is given by:

$$C_{JC}(u, v; \theta_t^L, \theta_t^U) = 1 - \left\{1 - \left[\left(1 - (1-u)^{\theta_t^U}\right)^{-\theta_t^L} + \left(1 - (1-v)^{\theta_t^U}\right)^{-\theta_t^L} - 1\right]^{-1/\theta_t^L}\right\}^{1/\theta_t^U},$$

with $\theta_t^L \equiv \theta^L(\boldsymbol{z}_t)$ and $\theta_t^U \equiv \theta^U(\boldsymbol{z}_t)$. The symmetrized Joe-Clayton copula entails lower- and upper-tail dependence coefficients, given by $\lambda_t^L \equiv \lim_{u\to 0} \frac{C_{SJC}(u,u;\theta_t^L,\theta_t^U)}{u} = 2^{-1/\theta_t^L}$ and $\lambda_t^U \equiv \lim_{u\to\infty} \frac{C_{SJC}(u,u|;\theta_t^L,\theta_t^U)}{u} = 2 - 2^{1/\lambda_t^U}$, respectively.

[5] Interestingly, variations in the upper-tail dependence may affect the estimation of the conditional lower-tail dependence and vice-versa. This means that we cannot ignore the former even if our interest lies primarily on the lower-tail dependence. This is why we employ the symmetrized Joe-Clayton copula rather than focusing on the lower tail dependence by means of either the Clayton or the rotated Gumbel copulae. We thank Andrew Patton for calling our attention to this point.

It now remains to specify how the conditional tail dependence parameters evolve over time. We assume that λ_t^L and λ_t^U are functions of market uncertainty, which we proxy using a single index that combines the term spread, the swap 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 swap spread gauges credit risk and counterpart risk by means of the difference between the interest rates on interbank loans and on short-term U.S. government debt (Brunnermeir, 2009). The VIX index is a model-free measure of the options-implied volatility of the S&P 500 Index. As such, it essentially provides the ex ante risk-neutral expectation of the future volatility. 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 (Corradi, Distaso, and Mele, 2008; Bollerslev, Gibson, and Zhou, 2009). Drechsler and Yaron (2008) 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 (2009) 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 model the time-varying nature of the tail dependence by:

$$\lambda_t^j \equiv \lambda^j(\boldsymbol{z}_t) = \Lambda(\theta_0^j + \theta_1^j \,\mathrm{VIX}_{t-1} + \theta_2^j \,\mathrm{VOLPREMIUM}_{t-1} + \theta_3^j \,\mathrm{TERM}_{t-1} + \theta_4^j \,\mathrm{SWAP}_{t-1}), \quad (6)$$

where the logistic function $\Lambda(\cdot)$ ensures that the tail dependence coefficients lie in the unit interval, i.e., $0 < \lambda_t^j < 1$, for $j \in \{L, U\}$. To avoid convergence problems with the logistic function, we standardize the covariates by subtracting their mean and further dividing by their standard deviation.

We estimate the copula parameters by QML. 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). Finally, the Monte Carlo results in Appendix C also show that the asymptotic distribution of the QML estimator offers a very good approximation to its finite-sample counterpart, even if the dynamic copula is driven by highly persistent covariates.

To check how well the symmetrized Joe-Clayton copula model fits the data, we employ the joint hit test put forth by Patton (2006). This is similar to Christoffersen's (1998) procedure to assess forecast interval accuracy. As in Patton (2006), we examine by means of hit tests the empirical coverage of our copula-based models in several regions of the joint distribution support, namely, the lower 10% tail, the interval from the 10th to the 25th quantile, the interval from the 25th to the 75th quantile, the interval from the 75th to the 90th quantile, and the upper 10% tail. The empirical coverage tests indicate that our copula-based models fit well the tails in every instance and hence we report in Section 3.2 only the p-values for the hit test that considers jointly all of the above regions.

2 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 that is 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&P 500 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 U.S. Dollar Index (USDX) for currency markets. The latter gauges the trade-weighted value of the U.S. dollar relative to the six major world currencies: the euro, Japanese yen, Canadian dollar, British pound, Swedish krona, and Swiss franc. The VIX index is the options-implied volatility of the S&P 500 Index from the Chicago Board Options Exchange. We calculate the volatility risk premium as the difference between the realized and implied volatilities of the S&P500 Index and compute the realized volatility using 5-minute returns on the S&P 500 futures index. Finally, we measure the term spread by the difference between the yields of the 30-year and 3-month U.S. Treasuries, whereas the swap rate is the difference between the 3-month T-bill and the 3-month LIBOR rates.

Our sample runs from September 2004 to May 2008, yielding a total of 926 daily observations. Table 1 reveals that bond and equity returns are on average about 2.5%, even though volatility is twofold for the S&P500 Index. The negative average return of the USDX index reflects the weakening of the U.S. dollar, whereas the high average GSCI return mirrors the recent commodity boom. In addition, its standard deviation confirms the traditional view that commodity prices are among the most volatile assets (Kroner, Kneafsey, and Claessens, 1995; Pyndyck, 2004; Blattman, Hwang, and Williamson, 2007). As for higher-order moments, only the S&P 500 Index exhibits substantial excess kurtosis, whereas skewness is material for both equity and bond markets. In particular, skewness is negative for the S&P 500 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 display significantly higher 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 EMN 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 returns, due to performance smoothing and illiquidity exposure (Getmansky, Lo, and Makarov, 2004). With the exception of the DS style index, squared returns are also very persistent in the hedge fund sector. Altogether, these results justify 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&P 500 Index and some of the equity-based styles (e.g., EH and ED). Correlation with the commodity index is always positive, with the 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 (2010).

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&P 500 Index. CA, DS, and EMN 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 mainly among hedge-fund styles. There is significant upper-tail dependence with the S&P500 Index only for a few styles, while we find none with bond, commodity, and foreign exchange markets.

3 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 tail dependence among their standardized residuals using the symmetrized Joe-Clayton copula. In contrast to Boyson, Stahel, and Stultz (2010), we focus on the conditional tail dependence between hedge fund styles and broad market returns.

3.1 Filtering index returns

To allow for illiquidity exposure and 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. It is worth mentioning that filtering hedge fund returns by means of a full MA(22) specification does not change our qualitative results.

Table 4 reports the QML estimates for the different 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&P 500 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) show that hedge funds typically display higher levels of autocorrelation due to the combination of illiquidity exposure and performance smoothing. In addition, cyclical serial correlation may also arise from certain schemes for allocating gains and profits between the investor's account, management account, and provision account (Darolles and Gourieroux, 2009).

We account for performance smoothing and illiquidity concerns using the two measures proposed by Getmansky, Lo, and Makarov (2004). The first is the normalized MA(0) coefficient $\bar{\zeta}_0 = 1/\sum_{j=0}^{22} \zeta_j$, where ζ_j is the MA(j) coefficient and $\zeta_0 = 1$. It gauges the fraction of the "true" daily return that the reported return reflects. The second is the smoothing index $\sum_{j=0}^{22} \bar{\zeta}_j^2$, with $\bar{\zeta}_j = \zeta_j / \sum_{j=0}^{22} \zeta_j$, which measures overall illiquidity and performance smoothing. As expected, the smoothing index is lowest for the DS style at 0.330, reflecting that distressed securities are typically less liquid. This is consistent with the high degree of persistence that we observe in the DS returns (i.e., MA coefficients sum to 0.824), along with a normalized MA(0) coefficient of $\bar{\zeta}_0 = 1/1.824 = 0.549$. The latter means that the reported return for the DS style reflects only about 55% of the true daily return. In addition, the smoothing index is also substantially different from one for every industry index, as well as for the CA, M, and RVA styles, suggesting some exposure to liquidity risk and/or performance smoothing. In contrast, we find very little evidence of smoothing within the EH, EMN, and MA styles. These findings complement well Getmansky, Lo, and Makarov's (2004) smoothing analysis using hedge fund style indices from the TASS database. [6]

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 ($\widehat{\alpha} + \widehat{\beta} \approx 1$, with $0.026 \leq \widehat{\alpha} \leq 0.213$ and $0.749 \leq \widehat{\beta} \leq 0.970$). 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, M and MA join CA, DS, and EMN 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 find only a few hedge fund styles exhibiting tail risk exposure to equity markets. In particular, we fail to reject the null of unconditional lower-tail dependence with the S&P 500 Index at the 5% significance level for the RVA style and for the EW index. At the 1% significance level, we start failing to reject lower-tail dependence for the asset-weighted global index and for the EH and M styles.

3.2 Joint distributions

For every pair of hedge fund style/index and broad market standardized residuals, we estimate the symmetrized Joe-Clayton copula function with time-varying parameters driven by market uncertainty.

Tables 6 and 7 report the conditional copula parameter estimates for every hedge fund aggregate index and style, respectively. It is striking how the picture changes dramatically once we condition on market uncertainty, in that most hedge fund styles now seem to exhibit exposure to equity tail risk. Lower-tail dependence with the S&P 500 Index decreases in a significant manner with market uncertainty in the hedge fund industry, seemingly mitigating the likelihood of a diversification breakdown at times of falling stock markets.

[6] See `http://www.hedgeworld.com/download/tracked/lipper_tass_brochure.pdf` for more details.

We further address this issue in Section 3.4 to understand whether there is enough evidence to contradict the perception that hedge funds heavily contribute to financial contagion and hence to systemic risk.

Despite little evidence of unconditional tail dependence, the DS style displays conditional exposure to equity risk, which changes mainly with the volatility premium and with the term and swap spreads. While it increases with the former, the lower-tail dependence decreases with the latter. This is the only case in which tail dependence declines with the swap spread. The swap spread is an indicator of liquidity risk and so it should have a negative effect on the tail dependence if positions are short in illiquid stocks. That is precisely the case of hedge funds within the DS style. We also observe lower-tail dependence unambiguously decreasing with market uncertainty for the EH and ED styles, mainly through the volatility-based measures, as well as for the macro style via term spread. In contrast, the exposures of the MA and RVA styles to equity tail risk mount significantly with the term and swap spreads, respectively.

On the other hand, there is very little action in the upper tails. We indeed fail to reject the null hypothesis of constant upper-tail dependence for most hedge fund index returns. There is only evidence of time-varying upper-tail dependence with equity markets for the DS style and, to a lesser extent, for the MD index. In particular, they both decrease sharply with market uncertainty.

Figure 1 plots how the conditional lower-tail dependence with the S&P 500 Index evolves for hedge fund returns over time. In the first row, we observe that the aggregate indices behave very similarly, displaying lower-tail dependence that decreases with the volatility-based measures and with the term spread, but increases with the swap spread. Overall, lower-tail dependence seems to diminish with market uncertainty due to the dominance of the VIX and volatility premium effects. The only exception is due to the AR index. It features little lower-tail dependence, which mainly responds to the term premium.

The second and third rows in Figure 1 reveal a mixed pattern. On the one hand, most hedge fund styles exhibit a conditional tail dependence that declines with market uncertainty even if through different channels. In particular, the plots for the DS and M styles are more similar in shape to that of the AR index, whereas those for the EH and ED styles resemble more the behavior of the market directional index. This reflects not only the effort that hedge funds with 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&P 500 Index increases significantly with the term premium and the swap spread for the MA and RVA styles, respectively. This is not too surprising, given that spread trading is more likely to entail negative returns in periods of high volatility and illiquidity, i.e., greater market uncertainty. Because of 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, we find neither conditional nor unconditional tail risk exposure to bond and currency markets. Our copula analysis, however, reveals that the tail risk exposure of macro hedge funds to commodity prices increases with market uncertainty in both tails. This is consistent with Edwards and Caglayan's (2001) claim that commodity trading advisors and macro hedge funds provide protection to downside risk in the equity markets.

Our results withstand a number of different robustness checks. First, although we only report in Table 6 the results for the symmetrized Joe-Clayton copula, there is no qualitative change if one restricts attention to the lower tail by means of either a Clayton or rotated Gumbel copula. The coefficient estimates are always of the same sign and result in a similar degree of lower-tail dependence. Second, the hit test that we perform to assess the empirical coverage in the joint tails indicates that the symmetrized Joe-Clayton copula is flexible enough to capture the corresponding dependence structure. Third, a recursive analysis shows that the QML estimates of the copula coefficients are very stable over time, ensuring that our findings are 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.

Fourth, our empirical findings are also robust to different specifications of the copula model. Replacing the VIX index and the volatility risk premium with their variance-based counterparts does not have a qualitative impact on the results. Assuming a polynomial-type specification with both volatility and variance terms does not pay off either, in that only the volatility-based measures of market uncertainty remain significant. Finally, 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 qualitatively the outcome.

Altogether, the only hedge fund indices for which we fail to reject tail market neutrality, regardless of whether conditional or unconditional, are AR, CA, and EMN. 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.

3.3 Tail neutrality

In this section, we replace the S&P 500 Index with the family of Russell stock market indices to test whether tail neutrality still holds once we control for stock characteristics. In particular, we estimate the symmetrized Joe-Clayton copula models of conditional tail dependence for the Russell indices, along with their value and growth sub-indices.

The Russell 3000 broad market index measures the performance of the largest 3,000 U.S. firms representing about 98% of the investable U.S. equity market, whereas the Russell Top 200 Index considers only the largest 200 U.S. firms (about 65% of the total market capitalization). The Russell Midcap Index reflects the performance of the mid-cap segment of the U.S. equity universe by looking, approximately, at the smallest 800 firms within Russell 1000 Index (which contains the largest 1,000 firms in the U.S. 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 U.S. market). Finally, the Russell Microcap Index assesses the performance of the microcap segment (less than 3% of the total market capitalization) by including the smallest 1,000 securities of the Russell 2000 Index. The corresponding growth and value sub-indices also rank firms according to their price-to-book ratios and forecasted growth values.

There is not much evidence of tail dependence with the Russell indices regardless of the tail we examined. In particular, we find no copula parameter estimate that differs from zero at the usual levels of significance.[7] In fact, we cannot reject the null hypothesis of constant lower- and upper-tail dependence with the Russell indices for the AR, CA, or EMN styles.

[7] We do not report these insignificant estimates for brevity, although they are available from the authors upon request.

Informal inspection indeed seems to confirm that they are tail neutral with respect to the different segments of the equity market.

3.4 Systemic risk

The evidence that hedge funds seem to reduce their tail exposure to equity markets in times of uncertainty is somewhat at odds with the perception that they contribute to systemic risk. In principle, due to style convergence and multiple layers of leverage, hedge fund failures are likely to result in a cascade of margin calls and fire sales that could well destabilize financial markets in a severe fashion. Forced liquidation of relatively large positions not only entails heavy losses to creditors and counterparties, but also indirectly affects other market participants through asset price adjustments and liquidity dry-ups.

We conduct a simple correlation analysis to give some perspective on these systemic risk issues. The idea is simple. Hedge funds reduce their tail exposure to equity risk in times of market uncertainty either by voluntarily stepping leverage down or by forced liquidation. If the former, this sort of *uncertainty timing* would lead to a positive correlation between changes in lower-tail dependence and stock market returns. If the latter, we should expect a positive correlation between hedge fund index returns and changes in the lower-tail dependence given that fire sales usually entail heavy losses to the hedge fund. As fire sales normally take more than one day, we also compute correlations over a week.

Table 8 reveals that daily correlations with stock market returns are either negative or insignificant, whereas correlations with hedge fund style returns are either positive or insignificant. The picture changes at the weekly frequency. Correlation with changes in the lower-tail dependence is mostly positive for equity market returns, although there are a few exceptions. In particular, weekly correlation with the S&P 500 Index remains negative only for DS (as expected), while it is insignificant for the M and RVA styles. As before, the correlation between style returns and changes in the lower-tail dependence is either positive or insignificant (notably, for the DS, M, MA, and RVA styles). All in all, this suggests that the reduced exposure to equity tail risk in periods of uncertainty is more consistent with forced liquidations and fire sales.

The above correlation analysis is unconditional, however. Given that our measure of tail dependence is conditional on market uncertainty, it makes more sense to examine these correlations over time. Figure 3 plots rolling correlations between the changes in the lower-tail dependence with equity/commodity markets and the corresponding broad market returns. The correlation is mostly negative for the aggregate indices. The only exception is the AR index, which oscillates around zero and tends to be positive in times of low market uncertainty, while negative in periods of uncertainty. Only for the macro style is the correlation with equity markets positive most of the times, even if not very sizeable. This suggests there is little evidence supporting *uncertainty timing* in which hedge funds reduce their leverage and tail risk exposure in response to increasing market uncertainty.

Figure 4 displays rolling correlations between hedge fund returns and the changes in their tail risk exposure to equity/commodity markets. Although the correlations are close to zero for many styles, it is striking how the correlation becomes significantly positive in the wake of the credit crisis for the GL, EW, and MD aggregate indices, as well as for the EH style. In turn, the correlation is almost always significantly positive for the AR style. This seems to confirm the belief that hedge funds reduce their exposure to tail equity risk mainly thorough forced liquidations.

As an alternative to rolling correlations, we also compute conditional correlations given whether the single index that proxies for market uncertainty is either above or below its unconditional mean. The results are similar, in that we find little evidence of *uncertainty timing*, whereas there is some evidence consistent with fire sales as the main driver for the tail risk reduction. This is consistent with the evidence of dramatic selloffs put forth by Ben-David, Franzoni, and Moussawi (2010).

Two caveats are in order. First, the correlation analysis provides only indirect evidence of systemic risk. It is virtually impossible to determine conclusive evidence on systemic risk without portfolio holdings data. Second, although it concerns hedge fund indices, the correlation analysis also gives some insights about individual hedge funds because of style convergence and of how tail dependence aggregates within a style. Style convergence occurs when hedge funds end up with similar positions/tradings even if for different reasons (Fung and Hsieh, 2000). This is more likely to happen in times of market uncertainty, such as falling markets and liquidity dry-ups. This means that we should expect less dispersion across funds and hence style returns become closer to individual hedge fund returns. The properties of tail dependence also imply that the tail dependence coefficient of a hedge fund index is equal to the maximum coefficient of the component hedge fund returns. Altogether, this means that our results for hedge fund styles are actually conservative with respect to individual hedge funds.

3.5 Credit crunch

The original sample for the tail risk analysis does not include the peak of the recent financial crisis (September 2008). This is unfortunate, both because of the severity of the crisis and also because it actually represents a a tail event, with many hedge fund failures. Expanding the tail risk analysis to include the crisis period is not straightforward, however. It is indeed very difficult to model the conditional marginals of the broad-market returns, as well as of the hedge fund styles in a congruent manner once we include the crisis period in the sample. To avoid modeling the credit crunch as a structural break, we consider the sample from June 2008 to May 2010 separately.

Table 9 reports the main descriptive statistics, which differ substantially from the statistics within the non-crisis period. With the exception of the MA style, the mean return is negative across every hedge fund index and style, as well as for equity and commodity markets. Overall, the hedge fund sector did not suffer as much as equity markets, although styles such as CA and DS experienced heavy losses. As expected, the volatility is higher within the crisis period, though skewness does not change much (apart from the MA style). Kurtosis is higher as well, with exception to the EMN and M styles. It is interesting how the EMN style now features the lowest kurtosis (rather than the highest).

Despite the palpable changes in the moments, the main difference is in the autocorrelation patterns. The Ljung-Box Q-statistics indicate that, even though autocorrelation in squared returns diminishes to some extent, serial correlation dramatically increases especially for the hedge fund returns. The latter makes it very difficult to find a congruent model for the conditional mean within the class of AR processes. As a result, we carry out the copula analysis for the crisis sample using a full MA(22)-GARCH(1,1) specification for every hedge fund index/style.

Copula parameters usually result in statistically insignificant tail dependence.[8] All in all, we find very little evidence of tail dependence within the crisis period.

[8] These unreported estimates are of course available upon request.

4 Conclusion

This study 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 rise in bad times due to increases in their volatility, 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 time-varying volatility does not play a role. We nonetheless find that most hedge fund styles feature time-varying tail risk exposure to the S&P 500 Index, which is driven by market uncertainty even if they exhibit little unconditional tail dependence. In particular, the lower-tail dependence of the overall hedge-fund industry seems to decrease with market uncertainty, ensuring some diversification gains even within periods of falling stock markets. The only exceptions are the MA and RVA styles for which tail risk exposure to the S&P 500 Index increases as market uncertainty builds up.

Also, we cannot reject market tail neutrality for two hedge-fund styles, namely CA and EMN, as well as for the AR index. This result is robust to decomposing the U.S. 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 AR index seems slightly larger, though still very small, for indices that consider only mid-cap firms. Finally, we also find very little evidence of tail dependence of hedge funds with bond and currency markets. As for the commodity markets, we document that the macro style exhibits more tail risk exposure in periods of high uncertainty. This is not so surprising given that, in bear markets, macro hedge funds presumably increase their exposure to emerging markets, whose performance typically depends heavily on commodity prices.

Our findings cast 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 and, as such, it is hard to gauge the actual exposures to systemic risk. However, it is important to stress that focusing on tail *dependence* rather than on tail *correlation* provides a better picture given that it explicitly controls 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 Sklar's Theorem Extension to Conditional Distributions

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

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

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

B Details on the Estimation Strategy

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

$$\ell(\boldsymbol{\phi}_X,\boldsymbol{\phi}_Y,\boldsymbol{\theta}) = \sum_{t=1}^{T} \log f^{(X)}(x_t|\boldsymbol{z}_t;\boldsymbol{\phi}_X) + \sum_{t=1}^{T} \log f^{(Y)}(y_t|\boldsymbol{z}_t;\boldsymbol{\phi}_Y) + \sum_{t=1}^{T} \log c_t(u_t,v_t;\boldsymbol{\theta}). \tag{B.1}$$

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

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. Replacing u_t and v_t with their empirical counterpart is not without consequences. The estimation errors that arise while computing $\widehat{u}_t$ and $\widehat{v}_t$ affect the covariance matrix of $\widehat{\boldsymbol{\theta}}$ and hence standard inference on $\boldsymbol{\theta}$ is invalid.

To solve this problem, we use a simple conditional bootstrap procedure. In particular, we proceed as follows:

1. Transform the cross-dependent vector $(\widehat{u}_t, \widehat{v}_t)$ into independent uniform variates $(\widetilde{u}_t, \widetilde{v}_t)$ on the unit square $[0,1]^2$ for all $t = 1, \ldots, T$ using the probability integral transform implied by the conditional copula distribution given $\boldsymbol{z}_t$.

2. Draw B bootstrap artificial samples of the form $(\widetilde{u}_t^{(b)}, \widetilde{v}_t^{(b)})$ for all $t = 1, \ldots, T$.

3. Transform them into cross-dependent variates $(\widehat{u}_t^{(b)}, \widehat{v}_t^{(b)})$ using the inverse probability integral transform implied by the conditional copula distribution given $\boldsymbol{z}_t$.

4. Transform the vector $(\widehat{u}_t^{(b)}, \widehat{v}_t^{(b)})$ into $(\widehat{\eta}_{X,t}^{(b)}, \widehat{\eta}_{Y,t}^{(b)})$ using the inverse empirical cumulative distribution function for all $t = 1, \ldots, T$.

5. Estimate $\widehat{\boldsymbol{\theta}}^{(b)}$ by quasi-maximum likelihood for every bootstrap replication $b = 1, \ldots, B$.

We employ $B = 1,000$ artificial bootstrap samples. As B grows to infinity, the sample covariance matrix of $(\widehat{\boldsymbol{\theta}}^{(1)}, \ldots, \widehat{\boldsymbol{\theta}}^{(B)})$ entails a consistent estimator for the true covariance matrix of $\widehat{\boldsymbol{\theta}}$, allowing us to perform valid asymptotic inference on $\boldsymbol{\theta}$ (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.

C Finite Sample Behavior of the QML Estimator

Little is known about the finite-sample properties of the QML estimator in dynamic copula models, especially in the presence of highly persistent covariates. We thus run a small Monte Carlo experiment to shed more light on this issue. The design of the simulation is as follows. In each Monte Carlo replication, we draw a sample of size $T = 1,000$ from the conditional symmetrized Joe-Clayton copula given by (5) with:

$$\lambda_t^j = \Lambda(\theta_0^j + \theta_1^j \, z_{j,t}), \qquad j \in \{L, U\},$$

where $z_{j,t}$ is a zero-mean, unit-variance AR(1) process with Gaussian innovations. We set the autoregressive parameters to 0.95 at the upper tail ($j = U$) and to 0.99 at the lower tail ($j = L$). The remaining parameters read $\theta_0^L = 0.5$, $\theta_0^U = 0$, and $\theta_1^U = \theta_1^L = 0.5$. This configuration approximately reflects the degree of tail dependence we observe in the hedge fund data. Given that the conditioning variate $z_{j,t}$ is ancillary, we fix the AR(1) process throughout the 1,000 replications.

Table C.1 reports the bias, standard deviation, and root mean squared error of the QML estimator, whereas Figure C.1 compares its distribution to the asymptotic Gaussian distribution. It is apparent that QML entails unbiased estimators. It also turns out that precision is somewhat higher at the lower tail despite the fact $z_{L,t}$ is more persistent than $z_{U,t}$. Finally, even if the dynamic copula is driven by highly persistent AR processes, the asymptotic Gaussian distribution seems to offer a very good approximation of the QML estimator in finite samples.

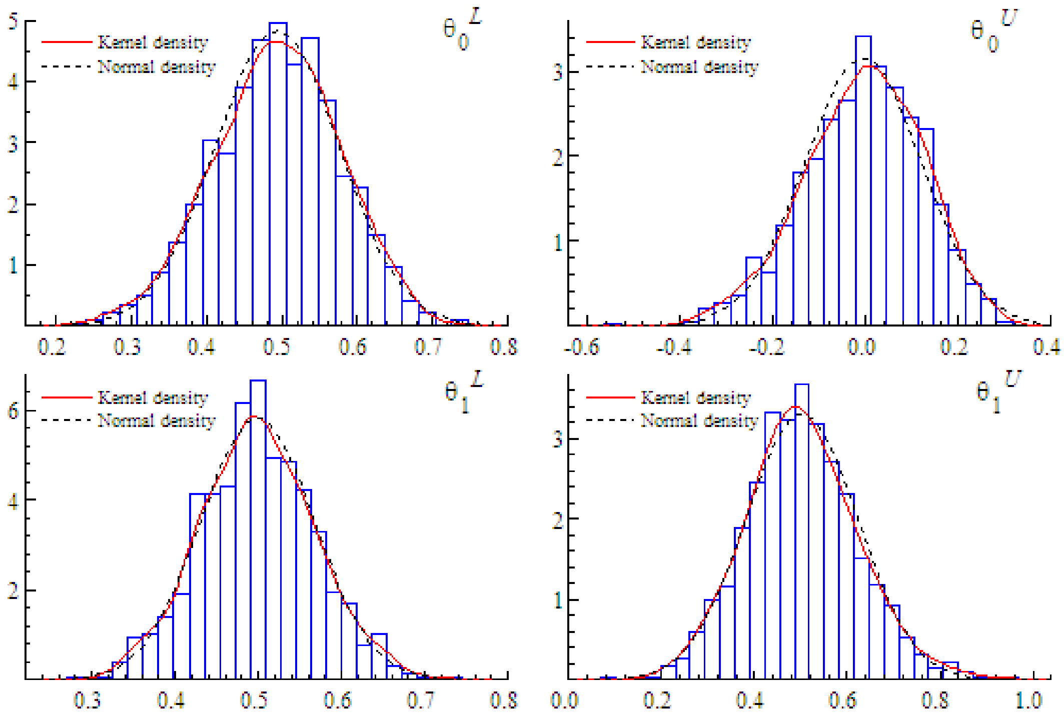

Figure C.1 The density of the QML estimator for a dynamic copula model with time-varying tail dependence driven by highly persistent AR(1) processes. The results refer to a sample size of $T = 1,000$ observations and hinge on 1,000 Monte Carlo replications.

	θ_0^L	θ_1^L	θ_0^U	θ_1^U
true value	0.500	0.000	0.500	0.500
bias	-0.006	-0.001	-0.005	0.002
standard deviation	0.083	0.068	0.126	0.120
root mean squared error	0.083	0.068	0.126	0.121

Table C.1 Monte Carlo results based on 1,000 replications about the QML estimator for a dynamic copula with time-varying parameters driven by highly persistent covariates.

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Table 1 Descriptive statistics for broad market returns and hedge fund returns for the September 2004 to May 2008 period.

Index	mean	standard deviation	skewness	kurtosis	minimum	maximum	$Q(20)$	$Q^2(20)$
S&P 500	0.03	0.86	-0.16	5.53	-3.53	4.15	37.8	396.7
Lehman Global Bond Index (LGBI)	0.02	0.42	0.12	3.46	-1.69	1.49	18.4	79.0
Goldman Sachs Commodity Index (GSCI)	0.09	1.44	-0.01	3.44	-4.76	6.54	17.9	61.3
U.S. Dollar (USDX)	-0.02	0.44	-0.09	3.42	-1.49	1.54	10.0	76.2
Global (GL)	0.02	0.26	-1.09	6.49	-1.39	0.81	63.1	536.1
Equal-Weighted (EW)	0.02	0.19	-1.43	9.58	-1.31	0.77	95.0	781.6
Absolute Returns (AR)	0.02	0.17	-0.87	10.9	-1.29	1.02	52.9	264.9
Market Directional (MD)	0.03	0.45	-0.92	5.91	-2.67	1.45	39.7	337.2
Convertible Arbitrage (CA)	0.00	0.25	-0.45	5.18	-1.05	1.05	53.2	218.6
Distressed Securities (DS)	0.02	0.15	-0.33	7.67	-1.01	0.63	145.3	47.6
Equity Hedge (EH)	0.02	0.40	-0.57	4.80	-1.83	1.50	39.3	448.1
Equity Market Neutral (EMN)	0.01	0.30	-0.29	28.9	-3.14	3.06	61.9	412.2
Event Driven (ED)	0.02	0.31	-0.75	6.46	-1.85	1.05	28.0	296.2
Macro (M)	0.03	0.52	-1.38	10.4	-3.71	1.99	50.9	510.4
Merger Arbitrage (MA)	0.03	0.24	-1.24	13.4	-1.75	1.34	37.9	744.3
Relative Value Arbitrage (RVA)	0.01	0.22	-0.67	15.2	-1.81	1.53	94.2	715.5

Notes: we report 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 Correlations between broad market and hedge fund returns for the September 2004 to May 2008 period.

	LGBI	GSCI	USDX	GL	EW	AR	MD	CA	DS	EH	EMN	ED	M	MA	RVA
S&P 500	-0.16	0.01	0.03	0.67	0.53	0.21	0.67	-0.16	-0.10	0.78	0.06	0.71	0.19	0.49	0.37
LGBI		0.07	-0.70	-0.07	-0.04	0.01	-0.04	-0.03	0.11	-0.11	-0.00	-0.14	0.09	-0.05	-0.07
GSCI			-0.21	0.27	0.28	0.32	0.29	0.06	0.01	0.19	0.10	0.17	0.36	0.07	0.17
USDX				-0.17	-0.19	-0.25	-0.17	-0.04	-0.15	-0.09	-0.10	-0.06	-0.29	-0.00	-0.13
GL					0.95	0.62	0.95	0.12	0.15	0.94	0.31	0.87	0.71	0.52	0.61
EW						0.68	0.88	0.27	0.24	0.82	0.46	0.82	0.75	0.57	0.62
AR							0.48	0.34	0.23	0.47	0.38	0.46	0.51	0.25	0.60
MD								0.03	0.13	0.90	0.26	0.84	0.73	0.51	0.46
CA									0.10	0.00	0.08	0.05	0.14	-0.03	0.18
DS										0.07	0.12	0.13	0.16	0.00	0.02
EH											0.24	0.85	0.49	0.53	0.49
EMN												0.23	0.22	0.12	0.25
ED													0.45	0.56	0.45
M														0.23	0.35
MA															0.31

Notes: 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.

Table 3 Results of the test for tail dependence between pairs of Index returns from September 2004 to May 2008.

	S&P 500	LGBI	GSCI	USDX	GL	EW	AR	MD	CA	DS	EH	EMN	ED	M	MA	RVA
S&P 500		0.194 (0.000)	−0.038 (0.000)	0.057 (0.000)	0.716 (0.059)	0.473 (0.000)	0.301 (0.000)	0.717 (0.060)	0.105 (0.000)	0.053 (0.000)	0.551 (0.009)	0.248 (0.000)	0.739 (0.085)	0.194 (0.000)	0.725 (0.072)	0.561 (0.004)
LGBI	0.084 (0.000)		0.252 (0.000)	−0.389 (0.000)	0.144 (0.000)	0.210 (0.000)	0.254 (0.000)	0.133 (0.000)	0.201 (0.000)	0.313 (0.000)	0.228 (0.000)	−0.024 (0.000)	0.191 (0.000)	0.208 (0.000)	0.095 (0.000)	0.247 (0.000)
GSCI	0.061 (0.000)	0.301 (0.000)		0.109 (0.000)	−0.095 (0.000)	0.026 (0.000)	0.212 (0.000)	−0.030 (0.000)	0.224 (0.000)	−0.044 (0.000)	−0.058 (0.000)	0.208 (0.000)	0.049 (0.000)	0.494 (0.001)	0.152 (0.000)	0.168 (0.000)
USDX	0.188 (0.000)	−0.376 (0.000)	0.126 (0.000)		−0.240 (0.000)	−0.068 (0.000)	0.047 (0.000)	−0.102 (0.000)	0.117 (0.000)	−0.016 (0.000)	0.059 (0.000)	0.114 (0.000)	−0.001 (0.000)	−0.044 (0.000)	0.156 (0.000)	−0.030 (0.000)
GL	0.754 (0.093)	0.136 (0.000)	0.246 (0.000)	0.088 (0.000)		0.867 (0.250)	0.618 (0.015)	0.877 (0.275)	0.198 (0.000)	0.026 (0.000)	0.755 (0.094)	0.627 (0.015)	0.904 (0.318)	0.450 (0.000)	0.618 (0.015)	0.780 (0.123)
EW	0.790 (0.141)	0.143 (0.000)	0.293 (0.000)	0.059 (0.000)	0.885 (0.289)		0.758 (0.079)	0.647 (0.021)	0.394 (0.000)	0.099 (0.000)	0.696 (0.045)	0.800 (0.147)	0.788 (0.139)	0.768 (0.108)	0.574 (0.006)	0.735 (0.075)
AR	0.592 (0.008)	0.302 (0.000)	0.405 (0.000)	−0.013 (0.000)	0.858 (0.235)	0.874 (0.263)		0.461 (0.000)	0.448 (0.000)	0.189 (0.000)	0.403 (0.000)	0.704 (0.056)	0.445 (0.000)	0.441 (0.000)	0.187 (0.000)	0.930 (0.369)
MD	0.697 (0.046)	0.278 (0.000)	0.319 (0.000)	0.042 (0.000)	0.896 (0.305)	0.824 (0.183)	0.699 (0.047)		0.178 (0.000)	0.149 (0.000)	0.801 (0.150)	0.472 (0.000)	0.818 (0.286)	0.323 (0.000)	0.621 (0.013)	0.570 (0.005)
CA	0.345 (0.000)	0.265 (0.000)	0.225 (0.000)	−0.084 (0.000)	0.604 (0.009)	0.653 (0.024)	0.769 (0.109)	0.514 (0.001)		0.188 (0.000)	−0.161 (0.000)	0.480 (0.001)	0.302 (0.000)	0.360 (0.000)	0.139 (0.000)	0.421 (0.000)
DS	0.233 (0.000)	0.353 (0.000)	0.443 (0.000)	0.184 (0.000)	0.300 (0.000)	0.346 (0.000)	0.479 (0.000)	0.406 (0.000)	0.650 (0.022)		0.089 (0.000)	−0.015 (0.000)	0.179 (0.000)	0.252 (0.000)	−0.089 (0.000)	−0.021 (0.000)
EH	0.728 (0.070)	0.014 (0.000)	0.249 (0.000)	0.051 (0.000)	0.836 (0.222)	0.948 (0.402)	0.749 (0.088)	0.793 (0.139)	0.408 (0.000)	0.397 (0.000)		0.531 (0.002)	0.816 (0.169)	0.305 (0.000)	0.596 (0.008)	0.520 (0.001)
EMN	0.562 (0.004)	0.243 (0.000)	0.323 (0.000)	−0.426 (0.000)	0.589 (0.009)	0.709 (0.054)	0.583 (0.009)	0.640 (0.019)	0.352 (0.000)	0.462 (0.000)	0.530 (0.002)		0.408 (0.000)	0.407 (0.000)	0.355 (0.000)	0.475 (0.000)
ED	0.699 (0.062)	0.214 (0.000)	0.315 (0.000)	0.133 (0.000)	0.759 (0.118)	0.935 (0.382)	0.644 (0.020)	0.808 (0.165)	0.528 (0.002)	0.317 (0.000)	0.827 (0.194)	0.518 (0.002)		0.122 (0.000)	0.736 (0.083)	0.560 (0.005)
M	0.759 (0.098)	0.450 (0.000)	0.515 (0.002)	0.175 (0.000)	0.934 (0.377)	0.938 (0.382)	0.865 (0.248)	0.980 (0.463)	0.399 (0.000)	0.389 (0.000)	0.839 (0.207)	0.620 (0.013)	0.862 (0.242)		0.259 (0.000)	0.565 (0.007)
MA	0.602 (0.009)	0.150 (0.000)	0.133 (0.000)	0.130 (0.000)	0.716 (0.059)	0.767 (0.107)	0.474 (0.000)	0.824 (0.188)	0.163 (0.000)	0.377 (0.000)	0.647 (0.022)	0.371 (0.000)	0.710 (0.059)	0.672 (0.032)		0.0795 (0.000)
RVA	0.960 (0.425)	0.131 (0.000)	0.293 (0.000)	0.055 (0.000)	1.017 (0.467)	0.983 (0.469)	0.948 (0.401)	0.389 (0.000)	0.553 (0.003)	0.324 (0.000)	0.684 (0.052)	0.702 (0.049)	0.773 (0.121)	0.984 (0.472)	0.554 (0.003)	

Notes: 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 Estimation results of marginal distributions.

	S&P 500	LGBI	GSCI	USDX	GL	EW	AR	MD	CA	DS	EH	EMN	ED	M	MA	RVA
μ	0.043 (1.99)	0.026 (1.96)	0.100 (2.19)	−0.026 (−1.94)	0.032 (3.36)	0.028 (4.05)	0.029 (4.90)	0.043 (2.46)	0.014 (1.74)	0.029 (3.92)	0.035 (2.56)	0.015 (2.37)	0.040 (3.86)	0.054 (2.45)	0.034 (6.59)	0.028 (4.02)
$\sum_{j=1}^{22} \zeta_j$	−0.078	0	0	0	0.330	0.403	0.400	0.213	0.256	0.820	0.152	−0.053	0.099	0.233	0	0.499
$\bar{\zeta}_0$					0.752	0.713	0.714	0.824	0.796	0.549	0.868	1.056	0.910	0.811	1	0.667
$\sum_{j=0}^{22} \bar{\zeta}_j^2$					0.591	0.539	0.532	0.696	0.657	0.330	0.771	1.134	0.836	0.677	1	0.464
ω	0.012 (1.68)	0.001 (1.07)	0.051 (1.42)	0.001 (1.09)	0.003 (1.90)	0.001 (2.26)	0.001 (1.79)	0.011 (1.80)	0.001 (2.04)	0.001 (2.10)	0.005 (2.36)	0.003 1.380)	0.002 (2.28)	0.014 (1.61)	0.002 (2.57)	0.001 (1.78)
α	0.055 (4.26)	0.026 (3.28)	0.038 (2.53)	0.028 (4.29)	0.101 (4.31)	0.124 (4.23)	0.159 (3.13)	0.074 (3.45)	0.059 (3.55)	0.097 (3.20)	0.089 (5.21)	0.213 (2.36)	0.091 (4.35)	0.208 (2.14)	0.208 (3.95)	0.138 (3.01)
β	0.926 (50.9)	0.968 (93.2)	0.937 (35.0)	0.970 (148.3)	0.851 (25.3)	0.837 (24.3)	0.802 (12.0)	0.863 (20.7)	0.927 (47.5)	0.851 (23.5)	0.875 (40.5)	0.749 (6.79)	0.879 (39.0)	0.749 (7.19)	0.764 (14.8)	0.849 (17.9)
$Q(40)$	31.6 (0.791)	37.3 (0.589)	38.3 (0.543)	43.4 (0.327)	34.2 (0.272)	32.7 (0.333)	33.3 (0.306)	38.7 (0.131)	25.8 (0.104)	26.6 (0.086)	39.2 (0.121)	34.0 (0.278)	37.2 (0.169)	24.7 (0.737)	21.4 (0.368)	23.8 (0.161)
$Q^2(10)$	11.4 (0.175)	10.8 (0.210)	10.5 (0.225)	14.8 (0.062)	3.24 (0.918)	4.24 (0.834)	8.48 (0.387)	1.44 (0.993)	8.34 (0.400)	2.79 (0.946)	6.45 (0.596)	8.13 (0.420)	10.0 (0.264)	1.81 (0.986)	5.41 (0.712)	4.77 (0.781)
$LM^2(10)$	1.17 (0.302)	0.96 (0.469)	1.09 (0.362)	1.48 (0.137)	0.30 (0.978)	0.41 (0.937)	0.84 (0.585)	0.13 (0.999)	0.78 (0.641)	0.22 (0.994)	0.80 (0.628)	0.77 (0.652)	0.95 (0.479)	0.18 (0.997)	0.52 (0.871)	0.45 (0.916)

Notes: We report quasi-maximum likelihood estimates, with the corresponding robust t-statistics within parentheses, for the intercept in the mean equation (3), as well as for every parameter in the variance equation (4). We also summarize the information concerning the MA coefficient estimates into three statistics. The sum of the MA coefficients $\sum_{j=1}^{22} \zeta_j$ gauges the strength of the serial correlation, whereas $\bar{\zeta}_0$ and the smoothing index $\sum_{j=0}^{22} \bar{\zeta}_j^2$, with $\bar{\zeta}_j = \zeta_j / \sum_{j=0}^{22} \zeta_j$ and $\zeta_0 = 1$, measure 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 is from September 2004 to May 2008.

Table 5 Results of the test for tail dependence between pairs of standardized residuals of Index returns from September 2004 to May 2008.

	S&P 500	LGBI	GSCI	USDX	GL	EW	AR	MD	CA	DS	EH	EMN	ED	M	MA	RVA
S&P 500		0.259 (0.000)	−0.003 (0.000)	−0.015 (0.000)	0.479 (0.001)	0.426 (0.000)	0.177 (0.000)	0.526 (0.002)	0.098 (0.000)	0.217 (0.000)	0.457 (0.000)	0.360 (0.000)	0.462 (0.000)	0.344 (0.000)	0.486 (0.038)	0.209 (0.005)
LGBI	0.185 (0.000)		0.268 (0.000)	−0.494 (0.000)	0.253 (0.000)	0.319 (0.000)	0.177 (0.000)	0.180 (0.000)	0.150 (0.000)	0.309 (0.000)	0.181 (0.000)	0.065 (0.000)	0.175 (0.000)	0.219 (0.000)	−0.069 (0.000)	0.202 (0.000)
GSCI	−0.133 (0.000)	0.263 (0.000)		−0.053 (0.000)	0.121 (0.000)	0.310 (0.000)	0.134 (0.000)	0.125 (0.000)	0.088 (0.000)	0.086 (0.000)	−0.004 (0.000)	0.250 (0.000)	0.053 (0.000)	0.469 (0.000)	0.141 (0.000)	0.186 (0.000)
USDX	0.209 (0.000)	−0.391 (0.000)	0.072 (0.000)		−0.270 (0.000)	−0.111 (0.000)	0.067 (0.000)	−0.104 (0.000)	0.059 (0.000)	0.112 (0.000)	−0.103 (0.000)	0.126 (0.000)	−0.262 (0.000)	0.099 (0.000)	0.051 (0.000)	−0.066 (0.000)
GL	0.672 (0.033)	0.323 (0.000)	0.309 (0.000)	0.098 (0.000)		0.960 (0.425)	0.471 (0.000)	0.789 (0.140)	0.225 (0.000)	0.395 (0.000)	0.769 (0.109)	0.452 (0.000)	0.785 (0.129)	0.531 (0.005)	0.121 (0.000)	0.482 (0.007)
EW	0.738 (0.078)	0.355 (0.000)	0.362 (0.000)	0.098 (0.000)	0.901 (0.312)		0.514 (0.001)	0.811 (0.163)	0.373 (0.000)	0.425 (0.000)	0.651 (0.023)	0.545 (0.004)	0.683 (0.042)	0.688 (0.041)	0.185 (0.000)	0.514 (0.002)
AR	0.482 (0.000)	0.286 (0.000)	0.294 (0.000)	0.113 (0.000)	0.617 (0.017)	0.593 (0.013)		0.367 (0.000)	0.418 (0.000)	0.369 (0.000)	0.304 (0.000)	0.431 (0.000)	0.463 (0.000)	0.426 (0.000)	0.109 (0.000)	0.859 (0.238)
MD	0.573 (0.006)	0.263 (0.000)	0.343 (0.000)	0.083 (0.000)	0.735 (0.075)	0.915 (0.337)	0.660 (0.027)		0.271 (0.000)	0.268 (0.000)	0.751 (0.102)	0.356 (0.000)	0.765 (0.119)	0.501 (0.002)	0.260 (0.000)	0.334 (0.000)
CA	0.345 (0.000)	0.131 (0.000)	0.237 (0.000)	−0.307 (0.000)	0.357 (0.000)	0.448 (0.000)	0.630 (0.027)	0.251 (0.000)		0.181 (0.000)	0.001 (0.000)	0.300 (0.000)	0.230 (0.000)	0.214 (0.000)	0.213 (0.000)	0.263 (0.000)
DS	0.054 (0.000)	0.201 (0.000)	0.294 (0.000)	0.135 (0.000)	0.467 (0.000)	0.453 (0.000)	0.581 (0.002)	0.476 (0.000)	0.610 (0.013)		0.295 (0.000)	0.098 (0.000)	0.334 (0.000)	0.318 (0.000)	0.074 (0.000)	0.307 (0.000)
EH	0.617 (0.017)	0.218 (0.000)	0.168 (0.000)	0.092 (0.000)	0.819 (0.176)	0.700 (0.048)	0.446 (0.000)	0.544 (0.005)	0.163 (0.000)	0.412 (0.000)		0.475 (0.000)	0.658 (0.032)	0.371 (0.000)	0.399 (0.000)	0.223 (0.000)
EMN	0.366 (0.000)	0.311 (0.000)	0.284 (0.000)	−0.175 (0.000)	0.366 (0.000)	0.513 (0.002)	0.515 (0.002)	0.402 (0.000)	0.349 (0.000)	0.300 (0.000)	0.334 (0.000)		0.379 (0.000)	0.240 (0.000)	0.139 (0.000)	0.307 (0.000)
ED	0.595 (0.008)	0.201 (0.000)	0.309 (0.000)	0.161 (0.000)	0.790 (0.134)	0.770 (0.119)	0.407 (0.000)	0.731 (0.072)	0.387 (0.000)	0.570 (0.000)	0.529 (0.002)	0.339 (0.000)		0.305 (0.000)	0.389 (0.000)	0.329 (0.000)
M	0.615 (0.014)	0.496 (0.000)	0.502 (0.000)	0.255 (0.000)	0.840 (0.206)	0.905 (0.320)	0.704 (0.051)	1.045 (0.419)	0.174 (0.000)	0.398 (0.000)	0.768 (0.108)	0.277 (0.000)	0.835 (0.206)		0.083 (0.000)	0.349 (0.000)
MA	0.550 (0.004)	0.131 (0.000)	0.118 (0.000)	0.102 (0.000)	0.483 (0.000)	0.366 (0.000)	0.399 (0.000)	0.573 (0.000)	0.187 (0.000)	0.346 (0.000)	0.593 (0.009)	0.193 (0.000)	0.529 (0.002)	0.338 (0.000)		0.041 (0.000)
RVA	0.750 (0.089)	0.165 (0.000)	0.223 (0.000)	0.092 (0.000)	0.772 (0.121)	0.685 (0.039)	0.600 (0.015)	0.621 (0.013)	0.087 (0.000)	0.303 (0.000)	0.674 (0.033)	0.332 (0.000)	0.551 (0.004)	0.530 (0.002)	0.452 (0.000)	

Notes: 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 Estimation results of the symmetrized Joe-Clayton conditional copula model for hedge fund indices.

aggregate index	QML coefficient estimates					Wald test	hit test
	constant	VIX_{t-1}	$VOLPREMIUM_{t-1}$	$TERM_{t-1}$	$SWAP_{t-1}$		
Global	0.417 (3.44)	−0.382 (−2.66)	−0.378 (−3.24)	−0.267 (−1.32)	0.258 (1.04)	0.001	0.640
	−0.157 (−0.55)	0.054 (0.18)	0.026 (0.13)	−0.135 (−0.28)	−0.385 (−0.73)	0.556	
Equal-Weighted	0.045 (0.36)	−0.393 (−2.36)	−0.119 (−0.96)	−0.396 (−1.71)	0.415 (1.40)	0.041	0.474
	−1.762 (−0.96)	0.603 (1.03)	−0.446 (−0.92)	−0.378 (−0.27)	−1.337 (−1.07)	0.564	
Absolute Returns	−1.987 (−1.51)	−0.396 (−0.41)	0.034 (0.06)	−0.466 (−0.37)	−0.006 (−0.01)	0.975	0.944
	−7.101 (−0.95)	0.248 (0.14)	−0.065 (−0.08)	−3.812 (−0.96)	−2.720 (−0.63)	0.906	
Market Directional	0.313 (2.38)	−0.533 (−3.10)	−0.180 (−1.43)	−0.713 (−3.12)	0.667 (2.32)	0.000	0.389
	−0.159 (−0.62)	0.032 (0.14)	−0.244 (−1.28)	−0.876 (−2.00)	0.179 (0.41)	0.070	

Notes: We model tail dependence between the S&P 500 Index and the different hedge fund indices by means of a symmetrized Joe-Clayton copula with time-varying parameters driven by market uncertainty. We report QML coefficient estimates and their bootstrap-based t-statistics within parentheses for both lower and upper tails (first and second rows, respectively for each aggregate index). In addition, we also document the p-values of the Wald test statistics for the null of constant either lower- or upper-tail dependence as well as of Patton's (2006) joint hit test. The sample period is from September 2004 to May 2008.

Table 7 Estimation results of the symmetrized Joe-Clayton conditional copula model for hedge fund styles.

broad market	hedge fund style	QML coefficient estimates: constant	VIX_{t-1}	$VOLPREMIUM_{t-1}$	$TERM_{t-1}$	$SWAP_{t-1}$	Wald test	hit test
S&P 500	Distressed Securities	−9.941 (−2.46)	0.597 (1.19)	0.678 (2.21)	−5.020 (−2.52)	−4.123 (−2.04)	0.000	0.394
		−79.51 (−3.62)	−23.06 (−1.95)	−29.47 (−3.66)	−22.37 (−1.87)	−8.264 (−2.06)	0.001	
	Equity Hedge	0.740 (6.74)	−0.284 (−2.31)	−0.315 (−3.04)	−0.164 (−0.89)	0.170 (0.75)	0.005	0.237
		0.323 (1.91)	−0.057 (−0.27)	0.069 (0.47)	−0.222 (−0.61)	−0.036 (−0.09)	0.563	
	Equity Market Neutral	−7.296 (−0.17)	−3.240 (−0.24)	2.227 (0.62)	2.288 (0.29)	−2.459 (−0.18)	0.879	0.964
		−9.425 (−0.43)	1.814 (0.28)	−0.470 (−0.35)	3.471 (0.33)	−8.937 (−0.59)	0.968	
	Event Driven	0.419 (3.49)	−0.398 (−2.80)	−0.351 (−2.95)	−0.038 (−0.19)	0.028 (0.11)	0.002	0.725
		−0.012 (−0.06)	−0.132 (−0.44)	−0.134 (−0.64)	−0.300 (−0.65)	0.253 (0.46)	0.877	
	Macro	−2.632 (−2.28)	−0.331 (−0.54)	0.362 (1.01)	−2.507 (−2.04)	0.856 (0.82)	0.163	0.653
		−13.76 (−1.73)	0.586 (0.33)	−1.729 (−1.34)	−12.19 (−1.88)	0.201 (0.06)	0.409	
	Merger Arbitrage	−0.546 (−2.95)	−0.280 (−1.22)	0.094 (0.58)	0.641 (1.91)	−0.344 (−0.83)	0.026	0.510
		−1.618 (−1.05)	0.478 (0.47)	−0.352 (−0.54)	0.216 (0.13)	−0.671 (−0.37)	0.956	
	Relative Value Arbitrage	−1.313 (−4.25)	0.126 (0.50)	−0.003 (−0.02)	−0.781 (−1.65)	1.163 (2.09)	0.003	0.456
		−7.038 (−0.16)	−1.511 (−0.11)	−0.782 (−0.13)	−0.354 (−5.80)	3.074 (0.25)	0.996	
GSCI	Macro	−1.946 (−3.95)	0.132 (0.45)	−0.156 (−0.79)	−0.852 (−1.55)	1.706 (2.39)	0.000	0.808
		−1.520 (−2.22)	1.144 (3.89)	−0.206 (−0.86)	1.661 (2.03)	−2.417 (−2.71)	0.001	

Notes: We model tail dependence between broad market indices and hedge fund style indices by means of a symmetrized Joe-Clayton copula with time-varying parameters driven by market uncertainty. We report QML coefficient estimates and their bootstrap-based t-statistics within parentheses for both lower and upper tails (first and second rows, respectively for each style). In addition, we also document the p-values of the Wald test statistics for the null of constant either lower- or upper-tail dependence, as well as of Patton's (2006) joint hit test. The sample period is from September 2004 to May 2008.

Table 8 Correlations between changes in the lower-tail dependence coefficient and returns on broad market and hedge fund Indices.

broad market	hedge fund index	broad market		hedge fund	
		daily	weekly	daily	weekly
S&P 500	Global	−0.098 [−0.163;−0.032]	0.394 [0.263;0.512]	0.014 [−0.051;0.079]	0.469 [0.346;0.577]
	Equal-Weighted	−0.124 [−0.188;−0.059]	0.552 [0.441;0.647]	0.122 [0.056;0.186]	0.555 [0.445;0.649]
	Absolute Returns	−0.030 [−0.095;0.035]	0.475 [0.352;0.581]	0.177 [0.113;0.240]	0.197 [0.051;0.334]
	Market Directional	−0.121 [−0.186;−0.056]	0.521 [0.405;0.621]	0.059 [−0.006;0.124]	0.549 [0.437;0.644]
	Distressed Securities	0.042 [−0.023;0.107]	−0.226 [−0.361;−0.081]	0.012 [−0.052;0.078]	−0.076 [−0.221;0.071]
	Equity Hedge	−0.091 [−0.155;−0.025]	0.394 [0.262;0.511]	0.000 [−0.064;0.066]	0.518 [0.402;0.618]
	Event Driven	−0.101 [−0.166;−0.036]	0.412 [0.282;0.527]	−0.019 [−0.085;0.046]	0.460 [0.336;0.569]
	Macro	0.075 [0.009;0.140]	−0.033 [−0.180;0.113]	0.074 [0.008;0.139]	−0.080 [−0.224;0.067]
	Merger Arbitrage	0.011 [−0.054;0.077]	0.174 [0.027;0.313]	0.019 [−0.046;0.085]	−0.000 [−0.147;0.146]
	Relative Value Arbitrage	0.005 [−0.060;0.071]	−0.052 [−0.197;0.095]	−0.065 [−0.130;0.001]	−0.018 [−0.165;0.128]
GSCI	Macro	0.019 [−0.046;0.085]	−0.038 [−0.184;0.108]	0.014 [−0.051;0.079]	−0.049 [−0.195;0.098]

Notes: We report sample correlations between changes in the lower-tail dependence coefficient and returns on either broad market or hedge fund Indices, with their 95% bootstrap-based confidence intervals within brackets. The sample period is from September 2004 to May 2008.

Table 9 Descriptive statistics for the S&P 500, GSCI, and hedge fund Index returns from June 2008 to May 2010.

Index	mean	standard deviation	skewness	kurtosis	minimum	maximum	$Q(20)$	$Q^2(20)$
S&P 500	-0.08	2.54	-0.08	5.98	-9.46	10.9	44.7	326.8
Goldman Sachs Commodity Index (GSCI)	-0.15	2.65	-0.09	3.50	-8.44	7.21	28.3	121.1
Global (GL)	-0.05	0.36	-1.12	12.1	-1.96	1.86	184.7	533.7
Equal-Weighted (EW)	-0.05	0.29	-1.38	14.5	-1.78	1.67	313.8	513.1
Absolute Returns (AR)	-0.04	0.21	-0.91	7.94	-1.21	0.69	29.9	41.6
Market Directional (MD)	-0.05	0.64	-1.15	12.4	-3.24	3.63	104.5	497.7
Convertible Arbitrage (CA)	-0.15	0.98	-2.47	13.6	-6.64	3.23	478.7	382.4
Distressed Securities (DS)	-0.13	0.47	-2.73	23.9	-4.33	1.72	47.7	2.14
Equity Hedge (EH)	-0.05	0.62	-0.75	7.62	-3.07	2.52	54.4	406.9
Equity Market Neutral (EMN)	-0.03	0.32	-0.15	3.44	-1.29	1.28	17.9	72.3
Event Driven (ED)	-0.03	0.49	-1.09	12.4	-3.16	2.54	58.7	371.5
Macro (M)	-0.04	0.47	-0.29	3.97	-1.61	1.53	21.6	68.7
Merger Arbitrage (MA)	0.02	0.56	2.05	35.1	-2.42	5.57	65.4	99.8
Relative Value Arbitrage (RVA)	-0.04	0.59	-1.09	14.3	-3.76	3.23	224.4	199.1

Notes: We document descriptive statistics for the S&P 500 Index and GSCI returns, as well as for the hedge fund Index returns from June 2008 to May 2010. $Q(20)$ and $Q^2(20)$ correspond to the Ljung-Box autocorrelation test up to lag 20 for returns and squared returns, respectively.

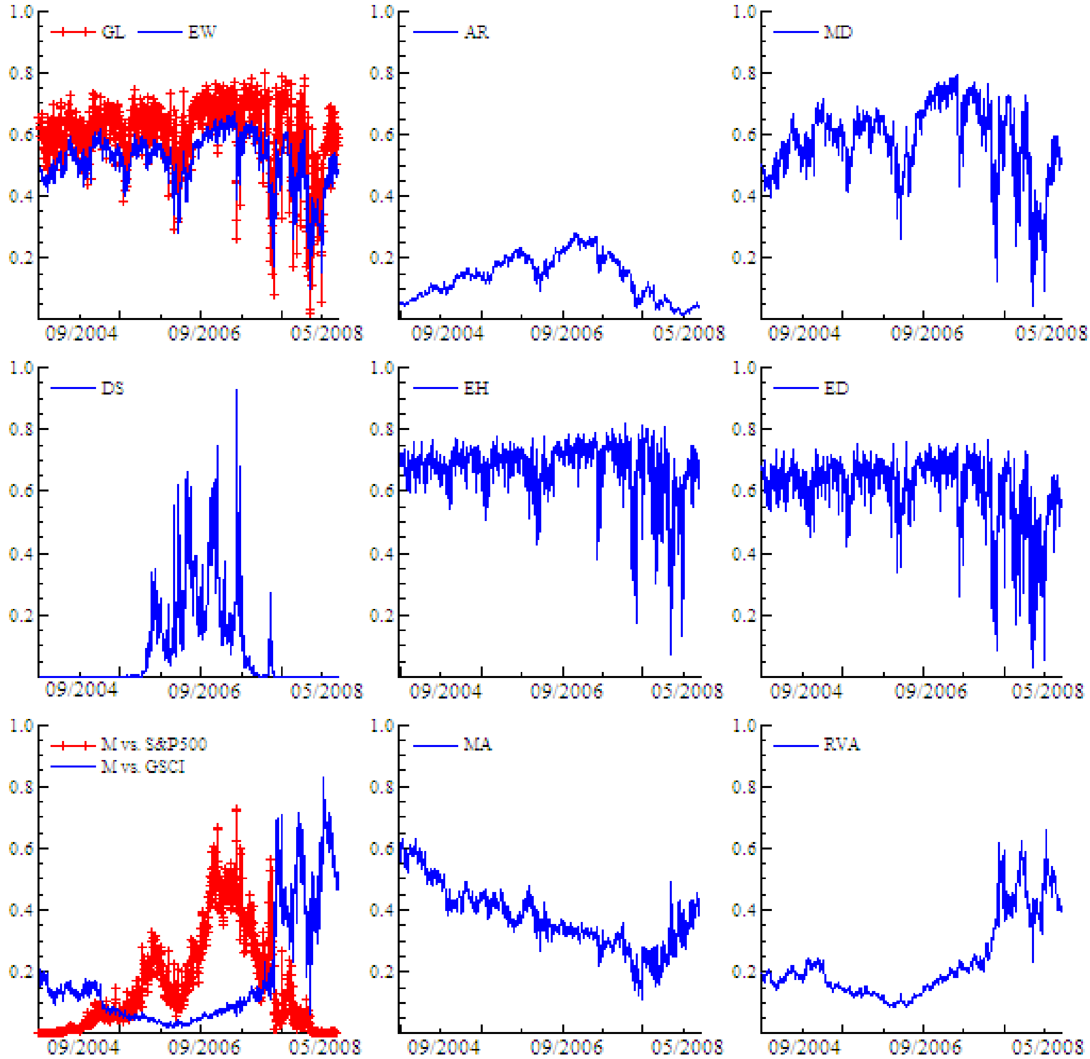

Figure 1 Lower-tail dependence between hedge fund styles and the S&P 500 Index from September 2004 to May 2008. For the macro style, we also display the evolution of the lower-tail dependence coefficient with the Goldman Sachs Commodity Index over time.

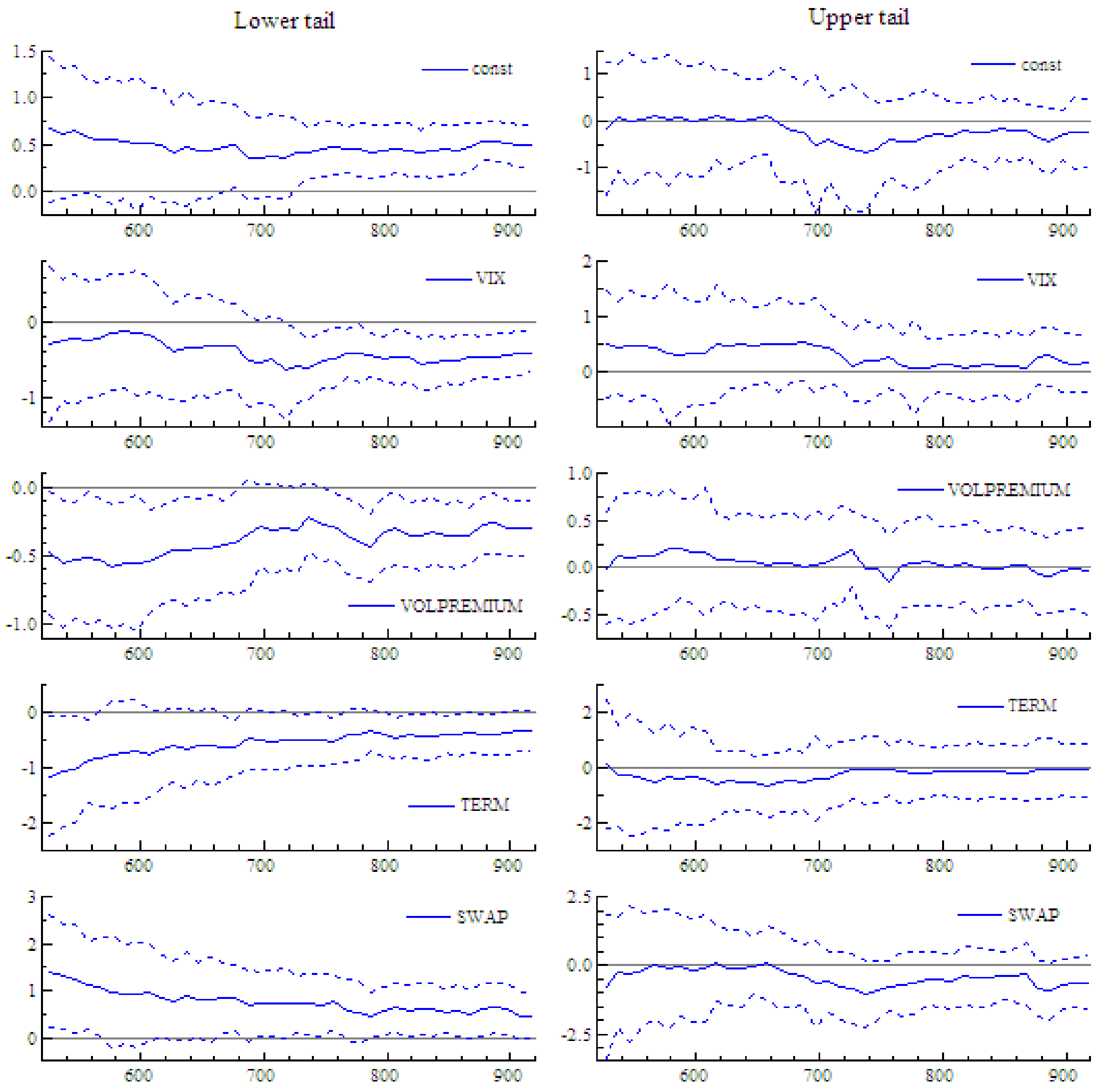

Figure 2 Recursive quasi-maximum likelihood estimates of the symmetrized Joe-Clayton copula parameters for the S&P 500 Index and HFRX Global Index, with their 95% bootstrap-based confidence interval.

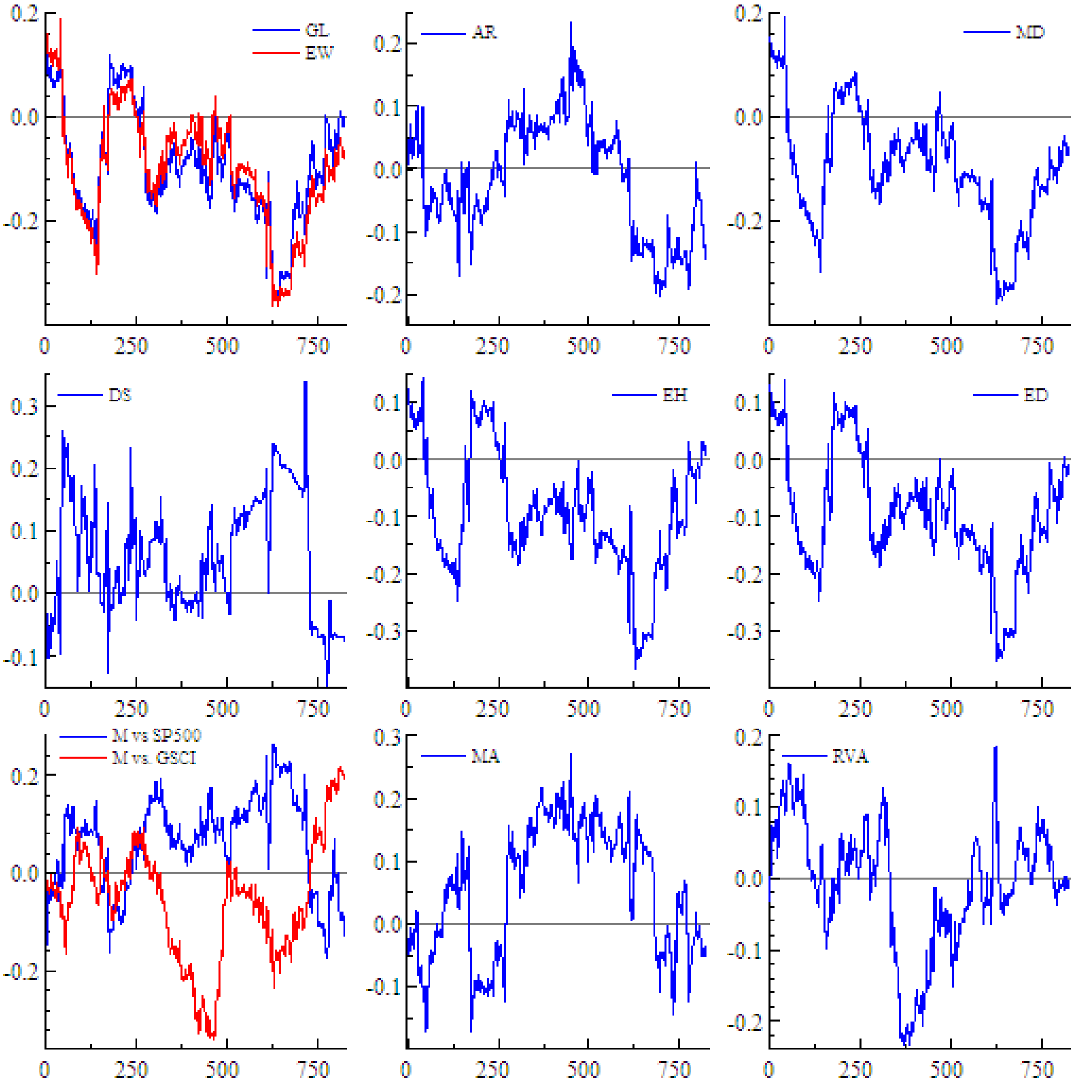

Figure 3 Rolling correlation between the S&P 500 Index returns and the changes in the tail risk exposure to equity markets from September 2004 to May 2008. For the macro style, we also display the rolling correlation between the Goldman Sachs Commodity Index returns and the changes in the tail equity risk exposure to commodity markets for the same period.

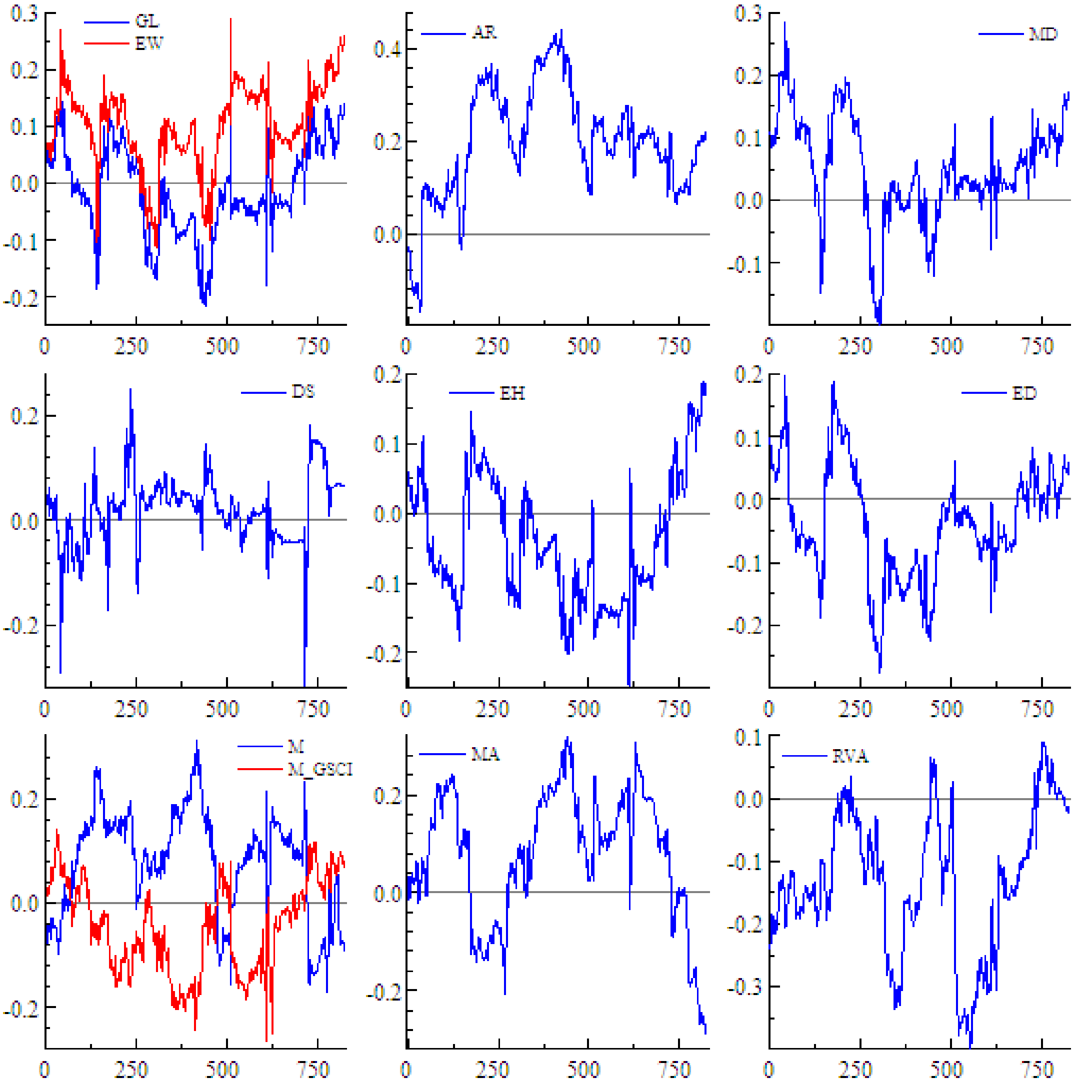

Figure 4 Rolling correlation between hedge fund returns and the changes in the tail risk exposure to equity markets from September 2004 to May 2008. We also display the rolling correlation between macro style returns and the changes in the tail equity risk exposure to commodity markets.