Hedge fund contagion, liquidity spirals and flight to quality

Evan Dudley *   Mahendrarajah Nimalendran †

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Abstract

We develop a novel approach that investigates the economic determinants of contagion among hedge funds. Our approach explicitly takes into account the left tail dependency between returns. We empirically investigate the relative importance of three economic channels that potentially explain contagion among hedge fund indices. We find that funding liquidity (proxied by margins on equity and currency futures contracts for members of the Chicago Mercantile Exchange), which captures the extent to which a fund can finance its positions, is a significant determinant of financial contagion. Our results on funding liquidity confirm the predictions made by Brunnermeier and Pedersen (2009) that market liquidity and funding liquidity interact to create liquidity spirals in which shocks to market liquidity reduce funding liquidity which in turn further reduces market liquidity. Our results also show that "flights to collateral" of the nature described in Fostel and Geanakoplos (2008) are a significant determinant of contagion among some types of hedge fund strategies. We find little support for the third channel, which is the consumption effect described Fostel and Geanakoplos (2008), whereby asset prices decrease because bad news about one asset class increases the price of risk for all securities.

Keywords: Hedge fund, contagion, asymmetric correlation, copula, flight to quality, liquidity

JEL classification: G31, G32

*University of Florida, Warrington College of Business Administration, Gainesville, Florida, 32611, USA. Email: evan.dudley@cba.ufl.edu. Tel: 352-392-9985.

†University of Florida, Warrington College of Business Administration, Gainesville, Florida, 32611, USA.

1 Introduction

The hedge fund industry has grown dramatically over the past two decades with estimated assets under management of $33 billion in 1990 and nearly $2 trillion in 2008. Part of the reason for this growth is that clients were promised 'absolute'(or positive) returns. Further, hedge funds supposedly offer portfolio diversification to investors because their investment style allows their returns to be uncorrelated with both equity market returns and with returns of hedge funds with different investment styles. However, in 2008 on average hedge funds lost 18% and the industry shrunk by a quarter reflecting both losses and client redemptions.

It is well known that correlations among equity markets are larger during large downward moves than during upward moves in equity prices. This phenomenon is generally referred to as contagion (Bekaert et al. (2005)). Can the same be said for hedge funds with different styles? Low correlation among different types of hedge funds motivate funds of hedge funds. The popularity of funds-of-funds is based on the notion that they offer the benefits of portfolio diversification by investing in hedge funds with different styles. The benefits of diversification are most important to investors during bad states. However, several studies including Boyson et al. (2008) have documented that hedge fund indices with different styles suffer from contagion. For instance in October 2008 the fifteen hedge fund style indices that are followed by CISDM all had negative returns ranging from -0.2% to -10%. More importantly the equity market neutral style index lost 2%!

In this study we examine the economic determinants of contagion as defined by asymmetric correlation among hedge funds, where the correlation conditional on negative returns of different hedge fund styles is much higher than the correlation conditional on positive returns. Our contribution is twofold. We develop a novel estimation procedure that captures co-dependency in the left tails of two return distributions. We also investigate the causal channels of contagion and show that the returns on highly levered portfolios also vary with funding liquidity, which we measure with changes in futures margins. Our findings are potentially important for empirical and theoretical asset pricing and for portfolio allocations. An example where the asymmetric correlation could be important is where agents have loss aversion preferences Barberis et al. (2001). These agents would treat gains and losses differently and are very averse to downside risk.

The first part of our analysis investigates whether the correlation of returns among hedge funds with different styles is higher conditional on low returns. We measure correlations conditional on being above or below a given quantile. We find that these exceedance correlations are much higher in the left tail of the distribution of hedge fund returns than in the right tail. Correlations are the most asymmetric for the distressed fund index, the merger arbitrage fund index, the relative value fund and the convertible debt fund. The neutral and macro index fund have the most symmetric correlations. We document that high correlations in the left tail occur during periods of high market volatility, as measured by the VIX (implied volatility on the S&P500 index options), during periods of low consumer confidence, and during periods of both high market and funding illiquidity.

We further explore the determinants of correlation between hedge fund returns by estimating the dependence structure between an index of hedge fund returns and the average return of the 7 other indices of hedge fund returns under consideration. Our dependence function (based on the bivariate normal distribution) is similar in nature to that employed in Longin and Solnik (1995) for international equity markets and Patton (2006) for currency markets. This type of dependence structure has the advantage that it yields a simple expression for correlation between two return series. It also allows time-varying correlation. We model the time-varying correlation as a function of the following exogenous variables: implied option volatility (measured by VIX), funding liquidity (measured by the margins on S&P500 futures contracts and USD/JY currency futures), market liquidity (Amihud measure), the Boyson et al. (2008) prime broker index, the TED spread (Libor minus T-Bill rate), corporate bond spreads and the Michigan consumer sentiment index.

We empirically examine the relative importance of three economic channels that may explain contagion or co-movement among hedge funds indices. The effect of the first two channels remains significant after we control for risk factors known to explain expected hedge fund returns. The first channel involves funding liquidity, which we measure by changes in futures margins for members of the Chicago Mercantile Exchange. Brunnermeier and Pedersen (2009) argue that margins are set according to fundamental value volatility and liquidity-based volatility. They show that under certain conditions, margins are destabilizing and funding liquidity and market liquidity are mutually reinforcing, leading to liquidity spirals. In figure 4 of Brunnermeier (2009), "funding problems force leveraged investors to unwind their positions causing 1) more losses and 2) higher margins and haircuts, which in turn exacerbate the funding problem and so on."

Our study demonstrates the importance of funding liquidity in explaining financial contagion. The impact of futures margins is both statistically and economically significant after controlling for other measures of funding liquidity. We find that changes in margins required for members of the CME on the S&P500 futures contracts and USD/JY currency futures are a significant determinant of contagion among hedge funds. The return on a portfolio of prime brokers and the TED spread (Libor minus T-Bill) are neither statistically nor economically significant in our specifications. The importance of the futures contract margin suggests that the liquidity spirals of the type described in Brunnermeier and Pedersen (2009) are a potential channel for hedge fund contagion.

The funding liquidity channel is related to the "cash-in-the-market" pricing described in Allen and Gale (1994). In their model, asset volatility increases when liquidity shocks occur and prices are determined by the amount of cash in the market rather than future returns. Limited participation of the type described in that paper fits in nicely with the liquidity spiral hypothesis. Liquidity shocks lead to deviations from fundamental value, causing some funds to incur losses on existing positions which in turn may increase margins requirements, creating greater deviations from fundamental value as funds unwind some of their positions.

The second channel we study is the collateral channel. In addition to trading based on margins, funds can also purchase assets by borrowing money and using assets as collateral. Fostel and Geanakoplos (2008) argue that disagreement between different types of investors over asset values lead to what they call a liquidity wedge. This wedge is the difference between what optimists are willing to pay to borrow funds and what pessimists are willing to demand to lend funds. The greater the wedge, the lower the present value of cash flows but the greater the value of an asset as collateral. Fostel and Geanakoplos (2008) argue that flight to quality arises when this liquidity wedge is high and the dispersion of collateral values between assets is high. Therefore we expect greater left tail co-dependence among funds that trade in securities with low collateral values, such as in low-rated corporate bonds or in convertible bonds. As the collateral value of these types of securities deteriorates, speculators must post more collateral or unwind their positions, thereby leading to lower asset values among funds with positions in these types of securities. Our measure of the collateral channel is the monthly change in the spread between BAA rated corporate debt and 10-year Treasuries. This variable is a significant determinant of expected returns for hedge fund indices. Moreover, we find that this variable explains the correlation between hedge fund indices (in particular the distressed fund index), even after controlling for its effect on expected returns.

The third channel is the consumption channel described in Fostel and Geanakoplos (2008). This channel is related with the risk premium required by investors. Fostel and Geanakoplos (2008) suggest that contagion is also caused by a portfolio effect in which bad news about one asset class increases the marginal utility of consumption today, thereby increasing the rate of return required to invest in other assets classes (which depresses all asset prices). Our empirical results suggest that the consumption effect is not an important channel for contagion among hedge fund returns.

Our paper is closely related to Boyson et al. (2008) who also document contagion among hedge fund indices. Their results suggest that contagion is caused by funding liquidity proxied by the returns on an index of stock prices of prime brokers. This paper is different from their study in several ways. First, we model asymmetric dependence between funds in a way that explicitly takes into account the left tail co-dependency of hedge fund returns. Second, we identify three potential channels that explain contagion, and third, we use a different measure to proxy for funding liquidity. We also show that contagion is greater among funds that invest in assets with lower collateral values. These are the assets which are the most vulnerable to flights to quality of the type observed in the fall of 2008.

In a related paper, Billio et al. (2008) examine whether hedge fund exposure to risk factors varies across different volatility regimes. Ang and Bekaert (2002) document that correlations between international equity market returns increase during periods of high volatility and negative returns. Pastor and Stambaugh (2003) show that marketwide liquidity is a significant risk factor. Acharya and Pedersen (2005) show that security returns vary with the covariance of its market liquidity and the market return. In contrast our paper emphasizes how funding liquidity affects contagion among funds that employ leverage, such as hedge funds.

2 Data and methodology

We employ data on hedge fund indices from CS Tremont. Our data includes monthly returns on 6 strategy indices and 2 sub-strategy indices from January 1994 to December 2008. The indices are value weighted and are based on each fund's self-reported investment style. We consider the following strategy indices: long/short, event driven, global macro, emerging markets, distressed debt, risk arbitrage, equity market neutral, and convertible arbitrage. Appendix A describes each strategy in detail.

We obtain time series returns for the S&P500 index. Individual stock and volume returns used to compute market illiquidity are provided by CRSP. Historical interest rates are obtained from Datastream and the returns on the Dow Jones Wilshire index are obtained from Morningstar. We obtain the maintenance margins for members of the Chicago Mercantile

Exchange (CME) from this exchange. These margins represent the amount of equity futures investors must hold in their accounts. These margins are different from margins members require from their clients. Client margins may vary according to members' assessment of the clients' ability to support a given futures position. We do not have information on client margins. Because of the long history of the futures contracts with the S&P500 and USD/JY currency futures contracts with the CME echange, we focus on these two contracts as measures of funding liquidity.

We construct our primary measure of funding liquidity by calculating changes in margins as a percentage of the underlying contract value. The monthly change in margins for futures contract on the S&P500 is denoted $chmrgsp$. The monthly change in margins on the futures contract on the USD/JY exchange rate is denoted $chmrgjy$. We provide details of how these measures are calculated in Appendix B.

Figure 5 shows the level of both futures margins alongside the S&P500 implied volatility index (VIX). Margins for both types of futures contracts increase during periods of high uncertainty, which confirms that margins are set according to market volatility. We further explore the impact these margins have on the contagion among hedge fund index returns.

Table 1 contains descriptive statistics on the various hedge fund index returns. Hedge fund index returns are positively correlated. They are also correlated with the S&P500 return. Figure 1 graphically display these correlations. The macro fund has the lowest correlation (0.262), while the long-short has the highest correlation (0.633). Surprisingly, the equity neutral fund, structured to have low correlations with the market, has quite a high correlation of 0.460 with the market.[1] The observed correlations with the S&P500 index are consistent with Patton (2009) who also finds that funds described as market neutral funds are positively correlated with market indices, although less so than other fund indices. Panel B shows the hedge fund betas with respect to the S&P500 index. The market neutral index

[1] The return series for the equity neutral index has a -40% return for the month of November 2008. We winsorize this outlier at the 0.5% percentile. The same style index provided by Hedge Fund Research has a positive 2% return during that month.

has the lowest beta at 0.09. The beta for this fund is low even though the correlation is high because the standard deviation of this return series is low.[2] The highest beta belongs to the emerging market index.

Hedge fund returns also exhibit considerable amounts of kurtosis, suggesting there are many observations in the tails of the distribution. Skewness is negative for all funds except the long-short fund index. The macro style fund has a relatively low (in absolute value) skewness coefficient.

Table 2 displays summary statistics for the explanatory variables. We attempt to capture funding liquidity with monthly changes in the margins (performance bonds) on traded futures contracts on the S&P500 stock index (chmrgsp) and the Japanese Yen contract (chmrgjy). Fluctuations in margin requirements reflect funding liquidity, or the extent to which investors can invest with a given amount of capital. Both types of margins are positively correlated. The S&P futures margins is positively correlated with the implied volatility index, VIX, and changes in corporate bond spreads. It is negatively correlated S&P500 index returns. Table 2 shows that the correlation between S&P500 margins and market illiquidity is positive (0.23). The correlation between JY futures and illiquidity is close to zero. The positive correlation between market liquidity and equity futures margins is consistent with Brunnermeier and Pedersen (2009) who demonstrate that margins are positively related to fundamental price volatility and market illiquidity.

Conversations with the risk management group at the Chicago Mercantile Exchange suggest that margins on futures contracts are set according to expected volatility on the corresponding stock index. In order to disentangle fluctuations in credit supply with volatility effects, we include the VIX, which is a measure of implied volatility of exchange traded options on the S&P500 index traded on the CBOE.

Our second measure of funding liquidity is the TED spread, which equals the spread between 3-month LIBOR and 3-month constant maturity Treasury bills. This spread measures

[2] $\beta = \frac{Cov(R_i,R_m)}{\sigma^2(R_m)}$. Therefore $\rho = \frac{Cov(R_i,R_m)}{\sigma_m \sigma_i} = \beta \frac{\sigma_m}{\sigma_i}$

bank credit risk. To the extent that banks have proprietary trading activities and also act as prime brokers to other hedge funds, we expect this measure to be positively associated with left tail correlations. Our third measure of funding liquidity, *pbi*, is the equal-weighted monthly return on a portfolio of prime-brokers and is derived from Boyson et al. (2008). This measure is negatively correlated with changes in margin requirements.

We also include monthly changes in the Amihud (2002) measure of stock market liquidity (*chilliqa*), the change in spread between BAA rated corporate bonds and 10-year Treasury bonds (BAAMTSY), and a consumer confidence measure from the University of Michigan, denoted $consconf$. This last measure is used to capture the consumption effect described in Fostel and Geanakoplos (2008).

We use the following factors to estimate the expected returns of each of the hedge fund indices. We include factors that have been shown to be correlated with hedge fund returns. Fung and Hsieh (2004) and Fung et al. (2004) show that the excess return on the S&P500 stock index (SNPMRF), the difference in returns between the Wilshire Small Cap 750 and the Wilshire Large Cap 1250 index (SCMLC), the spread between 10-year Treasuries and 3-month T-Bills (BD10RET) and the change in corporate yield spreads over 10-year treasury bonds (BAAMTSY) are statistically significant explanatory variables.

3 Conditional correlations

The correlations documented in table 1 are unconditional and therefore do not make a distinction between dependencies that are due to contagion. Detecting the presence of asymmetric correlation between hedge funds is important for portfolio allocation reasons. Investor portfolio allocation based on correlations measured in good states may overestimate the diversification within a portfolio of funds. In this section we examine conditional correlations between hedge fund indices and the CS Tremont all hedge fund index. We also examine the correlation between hedge fund indices and the S&P500 stock index return. In order to capture any possible asymmetry, we measure conditional correlations between hedge fund returns using the exceedance correlations used in Ang and Chen (2002). This method has the advantage of being simple to implement. It also allows us to measure the mean values of possible explanatory variables during bad states. Variables such as market illiquidity, funding liquidity, expected volatility and business conditions may be greater during bad states of the world, as defined by returns occurring in the left tail of their distributions.

Our analysis first examines whether correlations between hedge fund returns increase when members of pairs of funds both experience bad performance compared when they both experience good performance. More precisely, for a given percentile q and raw return series r_1 and r_2, we calculate the following conditional correlations:

$$\text{Left tail:} \quad corr(r_1, r_2 | r_1 < q, r_2 < q) \tag{1}$$

$$\text{Right tail:} \quad corr(r_1, r_2 | r_1 > q, r_2 > q). \tag{2}$$

Figure 2 display conditional or exceedance correlations for the left and right tails between fund indices and the S&P500 index. The median appears twice as we compute the correlation conditional on being above and below this quantile. Most funds display asymmetric correlations. Correlations with other funds are greater in the left tail than in the right tail for the distressed, risk arbitrage, long/short, event driven, convertible and emerging market funds. The macro and equity neutral funds display the least amount of asymmetric correlation.

Figure 3 shows similar graphs for exceedance correlations between fund indices and the CS Tremont All hedge fund index, which captures the universe of hedge funds tracked by CS Tremont. Again, the macro and equity neutral fund indices show the least amount of asymmetry.

For a given explanatory variable x, we also estimate

$$\text{Left tail:} \quad mean(x|r_1 < q, r_2 < q) \tag{3}$$

$$\text{Right tail:} \quad mean(x|r_1 > q, r_2 > q). \tag{4}$$

If there is no association between explanatory variable x and conditional correlations, there should be no difference between the conditional mean estimated over months associated with the left tail of the two return series and the conditional mean taken over months associated with the right tail of the two return series, i.e. the difference between these two means should be equal to zero.

Table 3 displays conditional means in the left and right tails (defined relative to the top and bottom 25th percentiles) for the comparison of the CS Tremont All hedge fund index and the S&P500 index. The last row displays the p-values for the difference in means between observations falling below the 25th and above the 75th percentiles. By construction, the excess return on the S&P500 is significantly more negative during tail events. Changes in corporate bond spreads are larger during left tail events, as are changes in market illiquidity. Consumer confidence is significantly lower in the left tail than in the right tail, while the VIX displays the opposite tendency. The prime broker index is also significantly lower in the left tail than in the right tail. Changes in margins are larger during bad states, but the difference is not statistically significant. Overall the exceedance means suggest that contagion between equity markets and hedge funds occurs during periods of high market uncertainty, low consumer confidence and high market illiquidity. Large differences in illiquidity and margins are consistent with the liquidity spiral hypothesis in Brunnermeier and Pedersen (2009). The observed differences in consumer confidence across left and right tail events, and in corporate bond spreads are consistent with the consumption and flight to collateral effects described in Fostel and Geanakoplos (2008).

4 Estimation framework

Our results on conditional correlations provide descriptive evidence that i) hedge fund return correlations are asymmetric, and ii) that correlations of hedge fund returns with equity markets are associated with decreases in bank credit quality, market liquidity and funding liquidity. We now proceed to formally model the dependence structure of returns between hedge fund indices. We model the time-varying correlation between hedge fund returns as a function of the explanatory variables described above. These variables are meant to capture the three economic channels that are posited to drive contagion among hedge funds. We also control for other possible determinants of time-varying correlation. The benefit of this approach is that it allows us to evaluate the impact of one variable on the dependence structure between two returns series, controlling for other possible covariates.

Our framework is similar to Longin and Solnik (1995) who model the correlation structure between international equity returns in a multivariate GARCH framework. We estimate the following bivariate system. The return process for hedge fund indices 1 and 2 is modelled as follows:

$$
\begin{aligned}
r_{1t} &= a_1 + b_1 r_{1t-1} + c_1' X_t + e_{1t}, \\
h_{1t} &= \omega_1 + \phi_1 e_{1t-1}^2 + \delta_1 h_{1t-1},
\end{aligned}
$$

$$
\begin{aligned}
r_{2t} &= a_2 + b_2 r_{1t-1} + c_2' X_t + e_{2t}, \\
h_{2t} &= \omega_2 + \phi_2 e_{2t-1}^2 + \delta_2 h_{2t-1},
\end{aligned}
$$

$$
\boldsymbol{e}_t \sim N(\mathbf{0}, H_t),
$$

with the variance equations $h_{jt}, j = 1, 2$ given above and the covariance equation as

$h_{12t} = \rho_t \sqrt{h_{1t} h_{2t}}$, where,

$$\rho_t = \Lambda \left(\alpha + \theta \rho_{t-1} + \gamma \frac{1}{10} \sum_{j=1}^{10} e_{1t-j} e_{2t-j} + \beta' W_t \right), \tag{5}$$

and $\Lambda(x) = \frac{2}{(1+e^{-x})} - 1$. The function Λ ensures that the correlation parameter, ρ_t, remains bounded between -1 and 1. The equation for the correlation includes a lagged value whose coefficient, θ, captures persistence in the correlation, a moving average term $MA(10)$ that captures past variation in the product of the residuals, and explanatory variables contained in a vector W_t. These explanatory variables are a dummy variable q that equals 1 when both time-t residuals are below their respective lower 25th percentiles, the change in market illiquidity *chilliqa*, the interaction of this variable with q, $chilliqaXq$, the change in credit spread BAAMTSY, changes in margins on equity futures $chmrgsp$ and currency futures $chmrgjy$, the interaction terms of these two variables with q, $chmrgspXq$ and $chmrgjyXq$, the TED spread, the prime broker index *pib*, the VIX implied volatility index and consumer confidence $consconf$.

Our approach is also similar to Longin and Solnik (2001) and Patton (2006) who model the dependence structure between two time series by estimating the copula between two distributions. The copula is a function that relates the marginal distribution of one time series to the marginal distribution of another time series. Copulas can be specified independently from the marginal distributions and remain invariant under increasing transformations of the underlying random variables. Many types of copulas are available. For example, Longin and Solnik (2001), Patton (2006) and Granger et al. (2006) employ a dependence function that has greater tail dependency in either the right or left tail. However these types of copulas do not give any indication on the economic causes of greater tail dependencies in one tail over another. Therefore we use instead the bivariate conditional normal copula function. Appendix B shows that multivariate GARCH with a bivariate normal distribution is a special case in which the copula function is bivariate normal.

5 Numerical estimation and empirical results

Our estimation procedure occurs in two stages. In the first stage we estimate the mean and variance equations, and in the second stage we estimate the correlation function given in equation (5). We model the mean and variance equation as an AR(1)-GARCH(1,1) process. We augment the return specification with X_t, which includes the excess return on the S&P500 SNPMRF, the size factor SCMLC, the change in credit spreads BAAMTSY and the term spread BD10RET. The autoregressive term is included to capture serial correlation in hedge fund returns documented in Getmansky et al. (2004) due to investments in illiquid assets with infrequent marking-to-market. The inclusion of the Fung and Hsieh (2004) risk factors is meant to control for common variation in expected returns across funds that is distinct from the economic causes of contagion between funds. The determinants of contagion are contained in the correlation equation (5). Our approach has the advantage of not relying on a moving window to estimate the correlation between funds. Moving window estimates, while simple to implement, vary greatly as tail observations enter and fall out of the window.

Equations (5) yields time varying estimates of the correlation based on the entire sample of observations. For example, the top panel of figure 4 shows the evolution of ρ_t, the correlation between the global macro fund index and the equal-weighted average of the 7 other indices, from January 1994 to December 2008. Our measure clearly captures increases in correlation between emerging markets funds and other fund indices during the 1998 LTCM crisis. The fitted correlation increased from -22% to 30% over the month of August 1998. However the correlation dropped from 75% to 34% in October 2008, before increasing back to 88% in December 2008. There is evidence of a structural break in both return volatility and correlation in March 2001. The bottom panel shows that the volatility of raw returns decreases but the correlation increased from -22% to 71% during the first quarter of 2001. The correlation remained high until October 2008.

5.1 Conditional mean and volatility

Table 4 shows the estimates of the conditional mean and variance equations. Hedge fund returns exhibit serial correlation. The coefficient on the lagged return is positive and significant across all indices. This result is consistent with Getmansky et al. (2004) who document similar autocorrelation in hedge fund returns. Additionally, all hedge fund returns are correlated with the excess return on the S&P500 index return. The long-short and emerging market funds have significant exposure to small stocks. The coefficient on SCMLC is positive for these two indices. The convertible arbitrage has a negative exposure to corporate bond spreads while the long-short strategy has a positive exposure to this risk-factor.

The variance equations show significant persistence in conditional volatility (garch(1)) for all funds except the event-driven index. The coefficient on lagged squared innovations (arch(1)) is positive and significant for the convertible arbitrage, emerging markets and macro funds only.

5.2 Determinants of contagion

The evidence presented so far has been descriptive in nature. This section investigates the causes of financial contagion among hedge fund indices. The three economic channels that we examine are 1), the funding channel which we measure with the monthly changes in equity and currency futures margins, 2) the collateral channel which we capture with changes in corporate bond spreads, and 3) the consumption effect which we measure with the consumer confidence index.

We estimate the determinants of the rank correlation between each hedge fund index and the average return over the 7 other funds for each of the following strategies: long-short (lgsh), event driven (evnt), global macro (macr), the distressed index (dist), risk arbitrage (risk), convertible debt (conv), equity neutral (neut) and emerging markets (emrg). Changes in futures margins and changes in illiquidity are interacted with a dummy variable that equals 1 when both returns are below their 25th percentiles. The purpose of this interaction variable is to capture differential effects on correlation in the left and right tails of the return distributions. The liquidity spiral hypothesis implies that liquidity spirals occur when hedge funds suffer losses on existing positions.[3] This formulation is analogous to the EGARCH model which permits asymmetry in the variance based on realized contemporaneous return residuals. In our case asymmetry occurs in the conditional correlation between the two return series.

The estimation results are presented in table 5. Marginal effects are shown in table 6. The marginal effects measure the slope of the correlation with respect to a given explanatory variable. While the sign of the estimated coefficients matches that of the marginal effects, it is not equal to the slope because of the transformation used to keep the correlation between -1 and 1. Marginal effects are measured by taking the first derivative with respect to a given variable and evaluation this derivative at the mean of the explanatory variables. The numbers in table 6 give the effect on the conditional correlation of a small increase in the chosen variable holding all else constant.

Correlation is persistent. The second row of table 5 shows that coefficient on lagged correlation is positive and significant at the 5% confidence level for 6 out of 8 indices. The fund with the most persistent correlation is the convertible arbitrage index. Correlation increases during bad states for 4 out of 8 style indices, as the coefficient on the dummy variable q is significant and positive. The effect of changes in market illiquidity is ambiguous. Market illiquidity is only statistically significant for the convertible and event driven funds and its sign is negative, which seems inconsistent with the hypothesis that divergence from fundamentals leads to liquidity spirals which causes contagion among hedge fund returns. A possible reason for the negative coefficient is that there is a lead-lag relation between market illiquidity and funding liquidity that is not captured in this specification. All our variables

[3]This dummy variable adds a look-ahead bias in the sense that we using information on historical returns over the entire data set to condition the correlation at time t. However, this method is simpler to implement than a more complicated model that separately parametrizes the left and right tails of the distribution.

are contemporaneous. Table 6 shows that illiquidity is positive and economically significant in the left tail for the global macro, long short and risk arbitrage funds. Its effect on the conditional correlation is negative for the other fund indices.

5.2.1 Collateral channel

Credit spreads BAAMTSY are negative and significant for the emerging markets fund, and positive and significant for the equity neutral fund. More importantly, table 6 shows that the effect of credit spreads on contagion is economically important for the equity neutral, distressed and risk arbitrage indices. The results for these three fund suggest that even after controlling for the effect of credit spreads on expected returns, contagion occurs through the collateral channel described in Fostel and Geanakoplos (2008). The effect of BAAMTSY on the convertible arbitrage fund, which invests in corporate debt securities is not statistically significant. However the effect of BAAMTSY on expected returns for this fund is significantly negative, which suggests that corporate bond spreads affect the returns through this strategy's exposure to corporate bond spreads, and not because of contagion and flight to collateral effects of the type described in Fostel and Geanakoplos (2008).

5.2.2 Consumption channel

The consumer confidence index is not an economically significant channel for contagion, although it is statistically negative for 3 out of 8 funds. These results suggest that the consumption effect whereby asset prices decrease because of higher risk premiums is not an important channel for contagion among hedge fund returns.

5.2.3 Funding liquidity channel

The estimates for the effect of futures margins offer substantial support for the liquidity spiral hypothesis of Brunnermeier and Pedersen (2009). The estimates for S&P500 futures are positive in the left tail for 7 out of 8 funds, the exception being the convertible arbitrage fund.

The coefficient on $chmrgXq$ is positive and statistically significant at the 10% confidence level for the equity neutral fund, the risk arbitrage fund, distressed debt and the macro fund. Interestingly the equity neutral fund has the largest exposure to equity margins in the left tail. Table 6 shows that the marginal effects for equity margins in the left tail equals 1.92, the next largest effect belonging to the risk arbitrage fund. Both of these funds style's involve significant exposure to equity markets, thus it is not surprising that they should be more exposed to funding liquidity related to equity futures contracts. The exposure of the macro fund is surprisingly large, given its stated strategy of investing in many types of assets classes other than those belonging to equity markets.

Table 5 show that margins on currency futures are statistically significant for 4 out of 8 funds. The marginal effect in the left tail of this variable is the highest for the equity neutral, risk arbitrage and global macro funds. The high coefficient in the left tail on currency future margins for the global macro fund is consistent with this funds strategy of investing in currency markets. This investment style exposes funds belonging to this category to margin constraints on currency futures. Figure 5 shows that margin level as a percentage of the contract notional value. The margins on currency futures are quite volatile and follow the VIX implied volatility index, even though the VIX is derived from equity options.

The marginal effects of the futures margins can be contrasted with that of the VIX itself and the prime broker index, *pbi*, neither of which has a large effect on the correlation between funds. The estimated sign on *pbi* is negative for 5 out of 8 funds, as economic intuition would suggest, although it is not statistically significant. A possible reason is the large volatility of this measure of funding liquidty. Table 2 shows that the volatility of this variable is 8.41% per month. Finally, the effect of TED spreads is negative, although the statistical significance for this variable is weak.

6 Conclusion

We examine 8 different indices of hedge fund returns based on managers' self-reported styles. We document asymmetric correlation between hedge fund returns over the period from January 1994 to December 2008. Asymmetry in correlations is associated with higher values of the VIX index, futures margins, TED spreads and corporate bond spreads.

We further investigate the determinants of contagion between hedge funds by modeling the dependence structure between these funds. We show that contagion among hedge fund returns occurs through 2 different channels. Consistent with the arguments made in Brunnermeier and Pedersen (2009) our finding suggest that contagion is caused by liquidity spirals that occur when shocks to market liquidity increase margins. The second channel is the collateral channel, which we measure with corporate bond spreads. The correlation between some fund strategies increases with corporate bond spreads. This evidence is consistent with the flight to collateral effect described in Fostel and Geanakoplos (2008). Our results on contagion are obtained after controlling for possible determinants of individual hedge fund index returns. Our results have implications for portfolio diversification. We show that a portfolio of hedge funds is diversified in good times, but not in bad times, which is precisely when diversification is most valued by a risk-averse investor.

One avenue which we leave unexplored is the degree to which individual funds are close to their borrowing constraints. Liquidity spirals should only arise if funds do not have enough equity to support their positions, thereby forcing them to unwind existing positions at a loss. A future avenue for research would be to measure the degree to which funding liquidity causes more severe contagion among funds that are constrained in this manner.

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7 Appendix A

We examine 6 hedge fund strategies and 2 sub-strategies. Classification definitions are obtained from CS/Tremont at: http://www.hedgeindex.com.

Long/short: Long/Short Equity funds invest on both long and short sides of equity markets, generally focusing on diversifying or hedging across particular sectors, regions or market capitalizations. Managers have the flexibility to shift from value to growth; small to medium to large capitalization stocks; and net long to net short. Managers can also trade equity futures and options as well as equity related securities and debt or build portfolios that are more concentrated than traditional long-only equity funds.

Event Driven: Event Driven funds invest in various asset classes and seek to profit from potential mispricing of securities related to a specific corporate or market event. Such events can include: mergers, bankruptcies, financial or operational stress, restructurings, asset sales, recapitalizations, spin-offs, litigation, regulatory and legislative changes as well as other types of corporate events. Event Driven funds can invest in equities, fixed income instruments (investment grade, high yield, bank debt, convertible debt and distressed), options and various other derivatives. Many managers use a combination of strategies and adjust exposures based on the opportunity sets in each sub-sector. The event-driven index includes the risk-arbitrage and distressed fund indices.

Macro: Global Macro funds focus on identifying extreme price valuations and leverage is often applied on the anticipated price movements in equity, currency, interest rate and commodity markets. Managers typically employ a top-down global approach to concentrate on forecasting how political trends and global macroeconomic events affect the valuation of financial instruments. Profits are made by correctly anticipating price movements in global markets and having the flexibility to use a broad investment mandate, with the ability to hold positions in practically any market with any instrument. These approaches may be systematic trend following models, or discretionary.

Emerging Markets: Emerging Markets funds invest in currencies, debt instruments, equities and other instruments of countries with emerging or developing markets (typically measured by GDP per capita). Such countries are considered to be in a transitional phase between developing and developed status. Examples of emerging markets include China, India, Latin America, much of Southeast Asia, parts of Eastern Europe, and parts of Africa. There are a number of sub-sectors, including arbitrage, credit and event driven, fixed income bias, and equity bias.

Equity Market Neutral: Equity Market Neutral funds take both long and short positions in stocks while minimizing exposure to the systematic risk of the market (i.e., a beta of zero is desired). Funds seek to exploit investment opportunities unique to a specific group of stocks, while maintaining a neutral exposure to broad groups of stocks defined for example by sector, industry, market capitalization, country, or region. There are a number of sub-sectors including statistical arbitrage, quantitative long/short, fundamental long/short and index arbitrage. Managers often apply leverage to enhance returns.

Distressed Restructuring: Event Driven funds that focus on distressed situations invest across the capital structure of companies subject to financial or operational distress or bankruptcy proceedings. Such securities trade at substantial discounts to intrinsic value due to difficulties in assessing their proper value, lack of research coverage, or an inability of traditional investors to continue holding them. This strategy is generally long-biased in nature, but managers may take outright long, hedged or outright short positions. Distressed managers typically attempt to profit on the issuers ability to improve its operation or the success of the bankruptcy process that ultimately leads to an exit strategy. This sub-index belongs to the event-driven index.

Risk Arbitrage: Risk Arbitrage Event Driven hedge funds attempt to capture the spreads in merger or acquisition transactions involving public companies after the terms of the transaction have been announced. The spread is the difference between the transaction bid and the trading price. Typically, the target stock trades at a discount to the bid in order to account for the risk of the transaction not closing successfully. In a cash deal, the manager will typically purchase the stock of the target and tender it for the offer price at closing. In a fixed exchange ratio stock merger, one would go long the target stock and short the acquirers stock according to the merger ratio, in order to isolate the spread and hedge out market risk. The principal risk is deal risk, should the deal fail to close. This sub-index belongs to the event-driven index.

Fixed Income - Convertible Arbitrage: Convertible Arbitrage funds aim to profit from the purchase of convertible securities and the subsequent shorting of the corresponding stock when there is a pricing error made in the conversion factor of the security. Managers typically build long positions of convertible and other equity hybrid securities and then hedge the equity component of the long securities positions by shorting the underlying stock or options. The number of shares sold short usually reflects a delta neutral or market neutral ratio. As a result, under normal market conditions, the arbitrageur generally expects the combined position to be insensitive to fluctuations in the price of the underlying stock.

8 Appendix B

Let L_t denote the level of the S&P500 stock index at the end of month t and $exch.rate_t$ denote the USD/JY exchange rate at the end of month t. Let $t = last$ denote the end of the last month in which margins were changed by the exchange. Thus,

$$M_t(S\&P500) = \begin{cases} M_{t=last}(S\&P500) & \text{if no change in margin during month t} \\ \frac{margin_t(S\&P500)}{L_t \times 500} \times 100 & \text{otherwise} \end{cases} \tag{6}$$

$$M_t(USD/JY) = \begin{cases} M_{t=last}(USD/JY) & \text{if no change in margin during month t} \\ \frac{margin_t(USD/JY)}{12{,}500{,}000/exch.rate_t} \times 100 & \text{otherwise} \end{cases} \tag{7}$$

$$chmrgsp_t = M_t(S\&P500) - M_{t-1}(S\&P500) \tag{8}$$

$$chmrgjy_t = M_t(USD/JY) - M_{t-1}(USD/JY) \tag{9}$$

$M_t(\bullet)$ equals the margin as a percentage of the underlying contract value as of the last time the exchange adjusted the required maintenance margin.

9 Appendix C

The return process for a hedge fund indices 1 and 2 is

$$
\begin{aligned}
r_{1t} &= a_1 + b_1 r_{1t-1} + c_1' X_t + e_{1t} \\
h_{1t} &= \omega_1 + \phi_1 e_{1t-1}^2 + \delta_1 h_{1t-1} \\
e_{1t} &= \sqrt{h_{1t}} \epsilon_{1t} \\
\epsilon_{1t} &\sim N(0,1)
\end{aligned}
$$

$$
\begin{aligned}
r_{2t} &= a_2 + b_2 r_{1t-1} + c_2' X_t + e_{2t} \\
h_{2t} &= \omega_2 + \phi_2 e_{2t-1}^2 + \delta_2 h_{2t-1} \\
e_{2t} &= \sqrt{h_{2t}} \epsilon_{2t} \\
\epsilon_{2t} &\sim N(0,1)
\end{aligned}
$$

Let $u_t = \Phi(\epsilon_{1t})$ and $v_t = \Phi(\epsilon_{2t})$. We model the dependence function $C(u_t, v_t)$ as a bivariate normal distribution. The bivariate normal copula equals,

$$C(u_t, v_t | X_{t-1}) = \int_{-\infty}^{\Phi^{-1}(u_t)} \int_{-\infty}^{\Phi(v_t)} \frac{1}{2\pi\sqrt{1-\rho_t^2}} \exp\left[\frac{-(r^2 - 2\rho_t rs + s^2)}{2(1-\rho_t^2)}\right] drds$$

where Φ^{-1} is the inverse cumulative standard normal CDF. As in Patton (2006), the evolution equation for ρ_t is

$$\rho_t = \Lambda\left(\alpha + \gamma \frac{1}{10} \sum_{j=1}^{10} \Phi^{-1}(u_{t-j}) \Phi^{-1}(v_{t-j}) + \beta' W_t\right) \qquad (10)$$

where $\Lambda(x) = \frac{2}{(1+e^{-x})} - 1$. The function Λ ensures that the correlation parameter remains bounded between -1 and 1.

Sklar's theorem yields

$$h(u,v) = f(u) g(v) c(u,v)$$

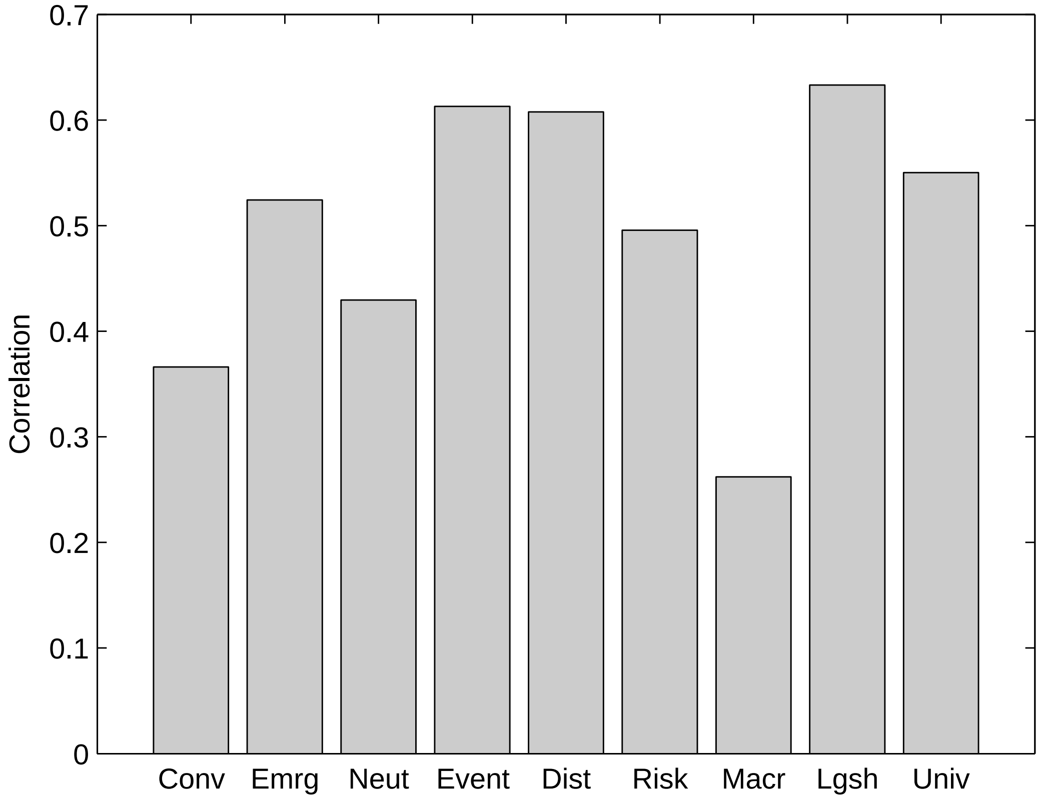
where h, f, g are the corresponding probability density functions for cumulative distribution functions F, G and H. c equals $\frac{\partial^2 C(u,v)}{\partial u \partial v}$. The log likelihood is therefore,

$$\ell(u, v, X | \alpha, \gamma, \beta) = \ln f + \ln g + \ln c$$

Estimation is performed in two steps. The first step estimates the AR(1)-GARCH(1) model by maximizing the log likelihoods $\ln f$ and $\ln g$. Taking cumulative normal distribution function to the standardized residuals from this model yields u_t and v_t. These residuals are then used in the likelihood function $\ln c$.

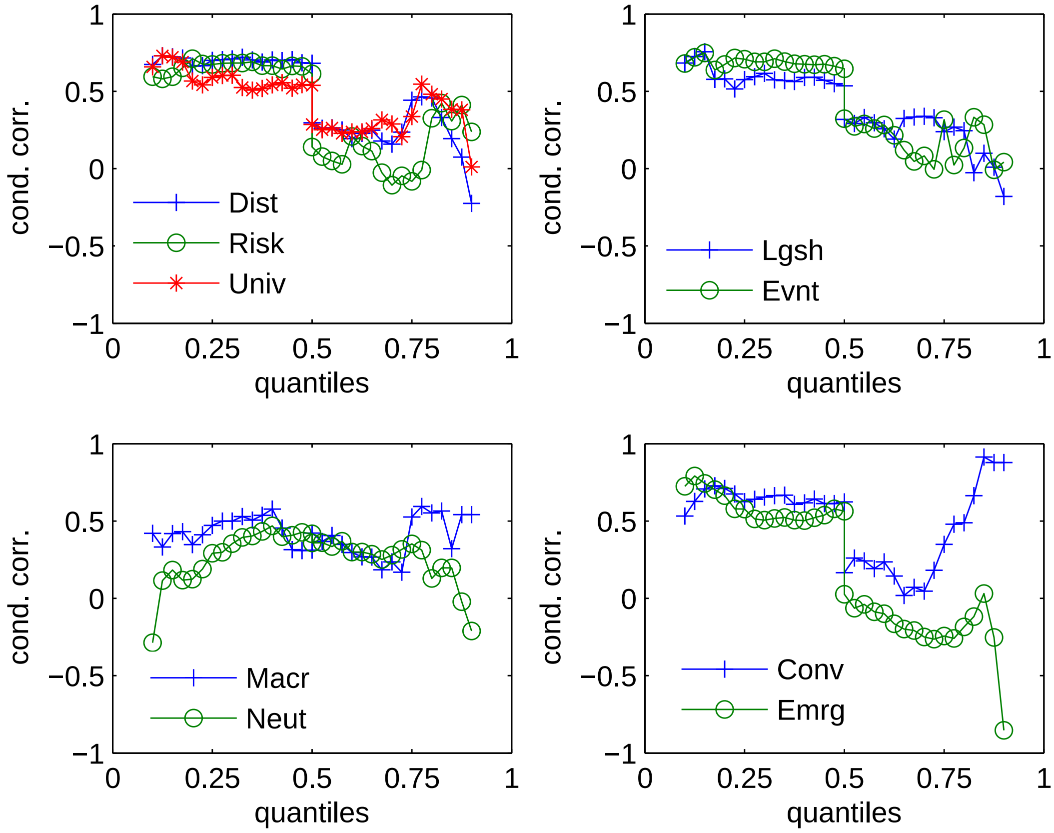
10 Tables and figures

Figure 1: Correlations between fund indices and S&P500



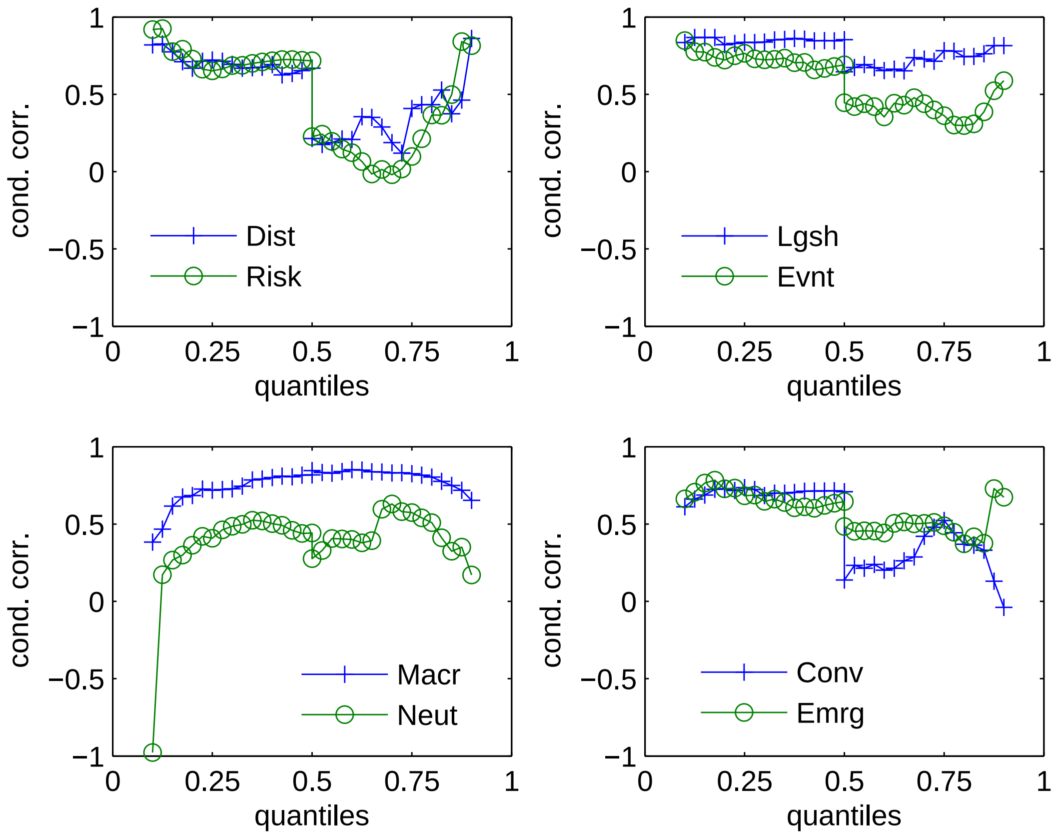
This figure displays correlations between raw monthly returns on a given hedge fund index with the S&P500. Univ represents the CS Tremont all hedge fund index. Other fund index descriptions are given in appendix A.

Figure 2: Exceedance correlations between fund indices and S&P500



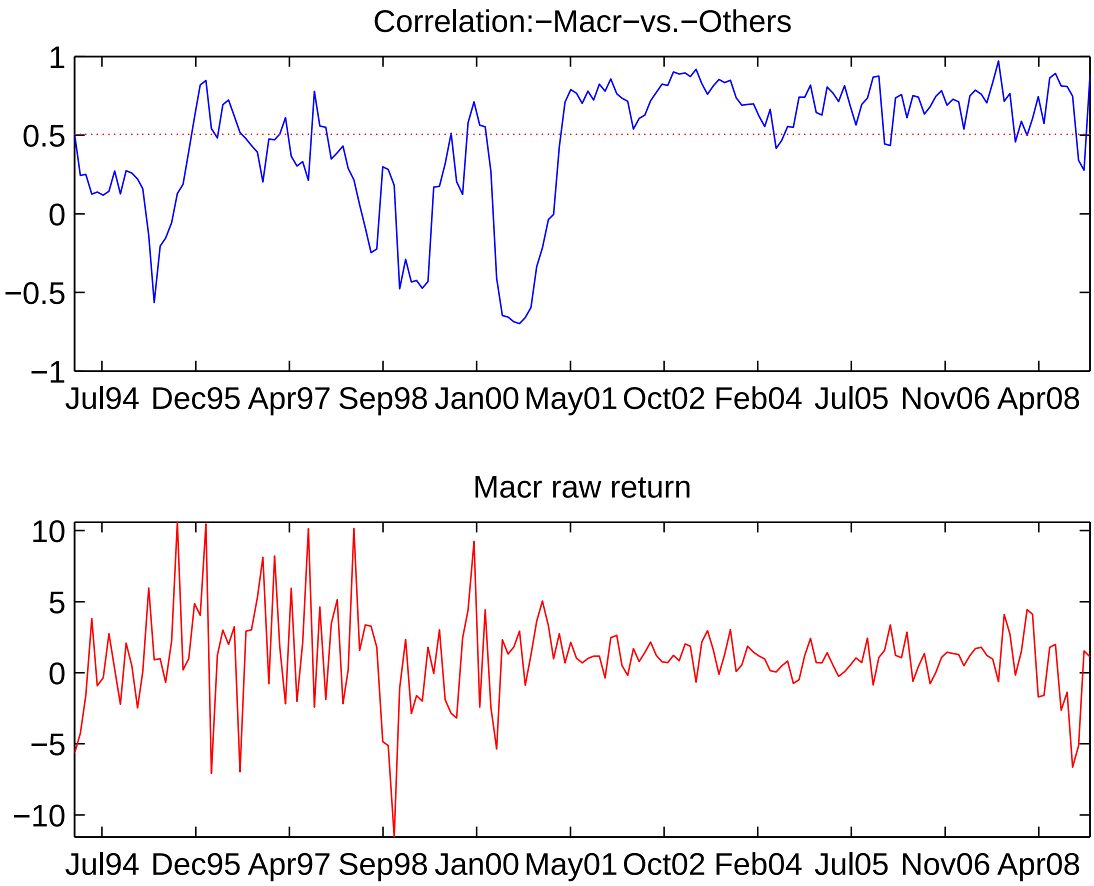
This figure displays exceedance correlations between raw monthly returns on a given hedge fund index with the S&P500. The x-axis indicates the percentile below or above which the observations are taken from. The y-axis display the corresponding exceedance correlation.

Figure 3: Exceedance correlations between fund indices and universe of funds



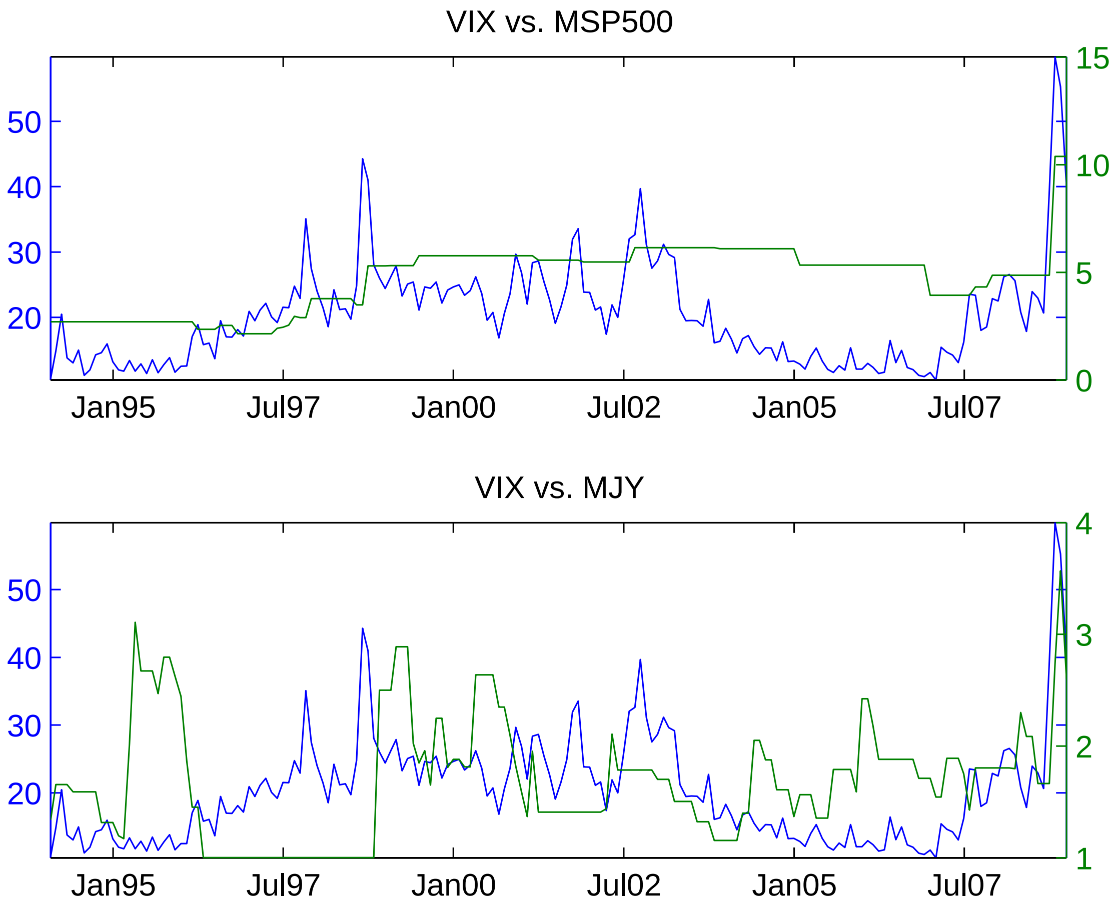
This figure displays exceedance correlations between raw monthly returns of different hedge fund indices with the all hedge fund index. The x-axis indicates the percentile below or above which the observations are taken from. The y-axis display the corresponding exceedance correlation.

Figure 4: Fitted correlation for universe and S&P500 index



Panel A displays the time-varying correlation, between the global macro fund index and the average return over the other 7 fund indices. Correlation values are fitted from MLE estimates of a bivariate normal distribution with correlates X. Panel B displays raw returns for global macro hedge funds index.

Figure 5: VIX vs MSP and VIX vs. MJY



This graph displays the VIX implied volatility index (jagged line) on the left hand axis and for the top panel, the margin on S&P500 contracts (step function) on the right hand axis. The bottom panel display the VIX and the margin on the USD/JY currency futures contract.

Table 1: Correlations between fund indices

This table display the correlation of monthly returns between various hedge fund indices from January 1994 to December 2008. *Dist* is the distressed hedge fund index, *Risk* is the risk arbitrage hedge fund index, *Neut* is the equity neutral hedge fund index, *Lgsh* is the long-short index, *Evnt* is the Event hedge fund index, *Macr* is the macro hedge fund index, *univ* is the all hedge fund index, *Conv* is the convertible arbitrage hedge fund index, *Emrg* is the emerging markets hedge fund index. *S&P500* is the return on the S&P500 stock index. All correlations are significant at the 1% confidence level.

Panel A: Hedge fund index return correlations

	Conv	Emrg	Neut	Evnt	Dist	Risk	Macr	Lgsh	univ	S&P500
Conv	1.000	0.422	0.440	0.665	0.602	0.481	0.371	0.439	0.542	0.366
Emrg		1.000	0.292	0.699	0.622	0.484	0.458	0.643	0.692	0.524
Neut			1.000	0.469	0.472	0.357	0.253	0.399	0.447	0.430
Evnt				1.000	0.939	0.676	0.421	0.717	0.740	0.613
Dist					1.000	0.575	0.356	0.638	0.661	0.608
Risk						1.000	0.223	0.569	0.477	0.496
Macr							1.000	0.467	0.835	0.262
Lgsh								1.000	0.820	0.633
univ									1.000	0.550
S&P500										1.000

Panel C: Means and variances

	Conv	Emrg	Neut	Evnt	Dist	Risk	Macr	Lgsh	univ	S&P500
beta	0.16	0.56	0.09	0.25	0.27	0.14	0.18	0.43	0.29	1.00
mean	0.46	0.65	0.71	0.78	0.86	0.58	1.03	0.82	0.73	0.46
SD	1.98	4.58	0.97	1.76	1.95	1.24	3.05	2.95	2.30	4.32
min	-12.59	-23.03	-5.69	-11.77	-12.45	-6.15	-11.55	-11.43	-7.55	-16.94
max	3.57	16.42	3.26	3.68	4.10	3.81	10.60	13.01	8.53	9.67
p25	-0.07	-1.70	0.27	0.12	0.14	0.04	-0.22	-0.83	-0.27	-2.01
p50	0.96	1.36	0.71	1.00	1.14	0.57	1.14	0.81	0.79	1.09
p75	1.42	2.85	1.28	1.84	1.96	1.30	2.33	2.33	1.88	3.36
kurt	22.01	7.48	12.97	17.35	15.00	7.90	5.93	6.40	5.26	4.40
skew	-3.53	-0.73	-1.45	-2.67	-2.37	-1.08	-0.03	0.02	-0.17	-0.81

Table 2: Summary statistics for explanatory variables

This table display summary statistics for various exogenous variables from January 1994 to December 2008. The variable SNPMRF equals the excess return of the S&P500 index. SMLC equals the difference in returns between the Dow Jones Wilshire small cap index and the Dow Jones Wilshire large cap index. BD10RET equals the spread between the 10-year constant maturity Treasury bond and the 3-month T-Bill. BAAMTSY equals the change in the spread between BAA rated corporate debt and the 10-year constant maturity Treasury bond. The variable *vix* is the implied volatility index on the Chicago Board of Trade S&P500 options, *chmrgsp* equals the monthly change in the margin on the S&P500 contract for CME members, *chmrgjy* equals the monthly change in the margin of the USD/JY currecy futures contract, *chilliqa* is the monthly change in the Amihud measure of illiquidity, *ted* is the spread between 3-month Libor and 3-month constant maturity Treasury bonds. The variable *pbi* equals the equal-weighted monthly return on a portfolio of bank stocks. Correlations in bold font are significant at the 5% confidence level.

Panel A: correlations

	SNPMRF	SCMLC	BD10RET	BAAMTSY	chmrgsp	chmrgjy	chilliqa	ted	cons	vix	pbi
SNPMRF	1.00	0.02	0.08	**-0.46**	**-0.23**	-0.11	**-0.26**	**-0.22**	**0.21**	**-0.43**	**0.84**
SCMLC		1.00	0.11	**-0.31**	-0.08	-0.12	**-0.29**	-0.13	0.00	-0.11	0.01
BD10RET			1.00	**-0.30**	-0.10	0.01	-0.11	**-0.58**	**0.21**	**-0.17**	0.10
BAAMTSY				1.00	**0.48**	**0.15**	**0.31**	**0.47**	**-0.20**	**0.45**	**-0.44**
chmrgsp					1.00	**0.25**	**0.23**	**0.40**	**-0.18**	**0.45**	**-0.25**
chmrgjy						1.00	0.00	**0.19**	-0.04	0.14	-0.09
chilliqa							1.00	**0.20**	-0.09	0.12	**-0.23**
ted								1.00	**-0.37**	**0.47**	**-0.29**
consconf									1.00	**-0.15**	**0.30**
vix										1.00	**-0.41**
pbi											1.00

Panel B: Means and variances

	SNPMRF	SCMLC	BD10RET	BAAMTSY	chmrgsp	chmrgjy	chilliqa	ted	cons	vix	pbi
mean	0.13	0.08	1.23	0.02	0.04	0.01	0.00	0.50	92.41	20.31	1.05
SD	4.30	3.12	1.33	0.19	0.46	0.29	0.16	0.43	11.33	7.84	8.41
min	-17.02	-15.11	-2.30	-0.51	-1.40	-0.97	-0.62	0.09	55.30	10.42	-32.99
max	9.23	15.39	3.98	1.19	5.52	1.50	0.54	3.13	112.00	59.89	24.91
p25	-2.30	-1.83	0.34	-0.07	0.00	0.00	-0.07	0.25	88.15	14.12	-3.76
p50	0.78	-0.02	1.09	0.01	0.00	0.00	-0.01	0.37	92.60	19.48	1.53
p75	3.03	1.97	2.38	0.08	0.00	0.00	0.08	0.55	99.85	24.20	6.48

Table 3: Means of liquidity variables in the tails

This table displays the mean values of each variable in the tails of the return distribution for the all hedge fund index (univ) and the S&P500 stock index. The left (right) tail is defined according to whether both index returns are below (above) the percentile of their respective time series in a given month. The variable SNPMRF equals the excess return of the S&P500 index. SMLC equals the difference in returns between the Dow Jones Wilshire small cap index and the Dow Jones Wilshire large cap index. BD10RET equals the spread between the 10-year constant maturity Treasury bond and the 3-month T-Bill. BAAMTSY equals the change in the spread between BAA rated corporate debt and the 10-year constant maturity Treasury bond. The variable *vix* is the implied volatility index on the Chicago Board of Trade S&P500 options, *chmrgsp* equals the monthly change in the margin on the S&P500 contract for CME members, *chmrgjy* equals the monthly change in the margin of the USD/JY currecy futures contract, *chilliqa* is the monthly change in the Amihud measure of illiquidity, *ted* is the spread between 3-month Libor and 3-month constant maturity Treasury bonds. The variable *pbi* equals the equal-weighted monthly return on a portfolio of bank stocks.

Quantile	SNPMRF	SCMLC	BD10RET	BAAMTSY	chmrgsp	chmrgjy	chilliqa	ted	consconf	vix	pbi
0.25	-5.56	-0.26	1.21	0.12	0.13	0.07	0.07	0.63	91.39	25.82	-8.50
0.5	-3.09	-0.05	1.17	0.07	0.06	0.00	0.03	0.53	90.83	22.73	-4.04
0.5	3.35	0.21	1.30	-0.03	0.02	0.01	-0.02	0.46	94.00	17.89	6.13
0.75	5.03	-0.42	1.22	-0.03	0.08	0.03	-0.03	0.51	96.33	20.55	9.27
pval	0.00	0.82	0.97	0.00	0.71	0.51	0.00	0.26	0.06	0.00	0.00

Table 4: First-stage estimates

This table displays estimates of first stage mean and variance equations for the CS Tremont hedge fund indices. AR(1) is the lagged value of the return. The variable SNPMRF equals the excess return of the S&P500 index. SMLC equals the difference in returns between the Dow Jones Wilshire small cap index and the Dow Jones Wilshire large cap index. BD10RET equals the spread between the 10-year constant maturity Treasury bond and the 3-month T-Bill. BAAMTSY equals the change in the spread between BAA rated corporate debt and the 10-year constant maturity Treasury bond. Numbers in bold font are significant at the 5% confidence level. p-values are in parentheses.

Panel A: mean equation

	conv	emrg	neut	evnt	dist	risk	macr	lgsh
const	**0.40**	0.16	**0.52**	**0.51**	**0.45**	**0.59**	**1.02**	**0.68**
	(0.04)	(0.63)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
AR(1)	**0.46**	**0.30**	**0.34**	**0.33**	**0.34**	**0.21**	**0.10**	**0.19**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.26)	(0.00)
SNPMRF	**0.07**	**0.57**	**0.09**	**0.23**	**0.26**	**0.13**	**0.19**	**0.47**
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)
SCMLC	0.03	**0.35**	0.01	**0.15**	**0.15**	**0.14**	0.08	**0.47**
	(0.36)	(0.00)	(0.78)	(0.00)	(0.00)	(0.00)	(0.29)	(0.00)
BD10RET	-0.09	0.10	-0.04	-0.02	0.05	**-0.13**	-0.10	-0.13
	(0.32)	(0.51)	(0.40)	(0.70)	(0.49)	(0.01)	(0.38)	(0.19)
BAAMTSY	**-2.93**	0.89	-0.11	-0.63	-0.21	-0.13	0.24	2.50
	(0.01)	(0.57)	(0.80)	(0.31)	(0.76)	(0.76)	(0.87)	(0.02)

Panel B: variance equation

	conv	emrg	neut	evnt	dist	risk	macr	lgsh
const	0.09	0.15	0.11	**0.30**	0.06	0.02	0.06	0.16
	(0.45)	(0.27)	(0.35)	(0.02)	(0.41)	(0.34)	(0.33)	(0.15)
arch(1)	**0.23**	**0.11**	0.12	0.71	0.15	0.12	**0.15**	**0.23**
	(0.04)	(0.05)	(0.22)	(0.21)	(0.06)	(0.08)	(0.01)	(0.00)
garch(1)	**0.77**	**0.88**	**0.73**	0.29	**0.85**	**0.86**	**0.85**	**0.73**
	(0.00)	(0.00)	(0.00)	(0.13)	(0.00)	(0.00)	(0.00)	(0.00)

Table 5: Determinants of contagion with equal weighted average of other hedge fund indices

This table displays maximum likelihood estimates of the determinants of the correlation between a given hedge fund index and equal-weighted average of the other 7 indices. AR(1) equals the lagged correlation, MA(10) equals the moving average of the past products of the first stage standardized residuals. q equals one when both both returns are below their respective bottom 25th percentiles. Other variable definitions are listed in table 3. Numbers in bold font are significant at the 5% confidence level.p-values are in parentheses.

	Conv	Emrg	Neut	Evnt	Dist	Risk	Macr	Lgsh
const	0.52	2.05	**1.53**	**2.26**	**2.40**	0.30	**2.94**	**2.11**
	(0.71)	(0.10)	(0.01)	(0.02)	(0.04)	(0.87)	(0.00)	(0.00)
AR(1)	**2.45**	0.99	**2.05**	**1.10**	**1.60**	-0.40	**2.08**	**2.07**
	(0.00)	(0.10)	(0.00)	(0.01)	(0.00)	(0.58)	(0.00)	(0.00)
ma(10)	**-0.60**	-0.25	-0.04	0.39	-0.27	-0.13	**-0.51**	-0.19
	(0.00)	(0.46)	(0.88)	(0.07)	(0.24)	(0.72)	(0.00)	(0.29)
q	**0.95**	0.63	0.75	**0.93**	**1.59**	**1.86**	0.13	0.10
	(0.00)	(0.09)	(0.16)	(0.01)	(0.00)	(0.00)	(0.73)	(0.79)
chilliqa	**-2.68**	-0.87	0.38	**-2.64**	0.29	-1.91	-1.36	-0.67
	(0.00)	(0.37)	(0.73)	(0.03)	(0.83)	(0.28)	(0.14)	(0.51)
chilliqaXq	-1.49	-0.05	-3.54	0.19	-3.83	2.21	2.71	3.00
	(0.65)	(0.98)	(0.23)	(0.88)	(0.09)	(0.38)	(0.28)	(0.10)
BAAMTSY	-0.56	**-2.76**	**1.45**	0.15	0.78	1.64	-0.87	-2.12
	(0.41)	(0.02)	(0.04)	(0.87)	(0.51)	(0.11)	(0.20)	(0.01)
ted	-0.03	0.07	-0.24	-0.35	-0.17	-0.04	-0.37	-0.19
	(0.82)	(0.86)	(0.34)	(0.32)	(0.62)	(0.91)	(0.08)	(0.36)
consconf	0.00	-0.01	**-0.02**	-0.01	-0.02	0.00	**-0.03**	**-0.02**
	(0.78)	(0.23)	(0.01)	(0.11)	(0.07)	(0.89)	(0.00)	(0.00)
chmarsp	0.35	**1.05**	**-1.32**	**-1.27**	**-1.49**	**0.78**	0.12	0.56
	(0.15)	(0.00)	(0.00)	(0.00)	(0.00)	(0.03)	(0.71)	(0.06)
chmarspXq	**-2.49**	-0.22	**6.20**	1.14	5.59	2.82	3.12	1.56
	(0.00)	(0.84)	(0.04)	(0.21)	(0.06)	(0.10)	(0.08)	(0.17)
chmarjy	**1.01**	-0.86	**0.84**	0.52	**1.77**	-0.44	**-1.10**	-0.28
	(0.01)	(0.16)	(0.05)	(0.36)	(0.00)	(0.54)	(0.01)	(0.52)
chmarjyXq	-1.98	2.04	0.82	1.39	-1.28	2.30	**3.12**	-0.82
	(0.13)	(0.25)	(0.50)	(0.18)	(0.34)	(0.20)	(0.02)	(0.43)
vix	0.01	0.00	0.02	-0.01	-0.01	0.01	0.02	0.01
	(0.65)	(1.00)	(0.04)	(0.65)	(0.52)	(0.72)	(0.07)	(0.37)
pbi	-0.03	-0.04	**0.07**	-0.02	0.01	0.00	-0.02	-0.03
	(0.22)	(0.06)	(0.00)	(0.27)	(0.63)	(0.94)	(0.24)	(0.04)
N	180	180	180	180	180	180	180	180

Table 6: Marginal effects evaluated at the mean of the explanatory variables

This table displays estimates of the marginal effect of each of the determinants of correlation between hedge fund indices. The marginal effect is obtained by taking the derivative of the correlation function with respect to a given variable and evaluating this result at the mean of the explanatory variables. Variable definitions are in Tab. 3. Panel B computes the marginal effect of each variable in the left tail by adding the effects for each term with its interaction with the dummy variable q in panel A.

Panel A: Marginal effects evaluated at the mean of the explanatory variables

	Conv	Emrg	Neut	Evnt	Dist	Risk	Macr	Lgsh
const	0.21	0.70	0.60	0.66	0.89	0.14	1.06	0.66
AR(1)	0.97	0.34	0.80	0.32	0.59	-0.19	0.75	0.65
ma(10)	-0.24	-0.08	-0.01	0.11	-0.10	-0.06	-0.18	-0.06
q	0.37	0.22	0.29	0.27	0.59	0.88	0.05	0.03
chilliqa	-1.06	-0.30	0.15	-0.77	0.11	-0.91	-0.49	-0.21
chilliqaXq	-0.59	-0.02	-1.39	0.06	-1.42	1.05	0.98	0.94
BAAMTSY	-0.22	-0.95	0.57	0.04	0.29	0.78	-0.31	-0.66
ted	-0.01	0.02	-0.09	-0.10	-0.06	-0.02	-0.13	-0.06
consconf	0.00	0.00	-0.01	0.00	-0.01	0.00	-0.01	-0.01
chmarsp	0.14	0.36	-0.52	-0.37	-0.55	0.37	0.04	0.18
chmarspXq	-0.98	-0.07	2.44	0.33	2.08	1.34	1.13	0.49
chmarjy	0.40	-0.29	0.33	0.15	0.66	-0.21	-0.40	-0.09
chmarjyXq	-0.78	0.70	0.32	0.40	-0.48	1.10	1.13	-0.26
vix	0.00	0.00	0.01	0.00	0.00	0.01	0.01	0.00
pbi	-0.01	-0.02	0.03	-0.01	0.00	0.00	-0.01	-0.01

Panel B: marginal effect in the left tail

	Conv	Emrg	Neut	Evnt	Dist	Risk	Macr	Lgsh
chilliqa	-1.65	-0.32	-1.24	-0.71	-1.31	0.14	0.49	0.73
chmarsp	-0.84	0.29	1.92	-0.04	1.52	1.71	1.17	0.66
chmarjy	-0.38	0.41	0.65	0.56	0.18	0.89	0.73	-0.35