Caught by the tail: Tail risk neutrality and hedge fund returns

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Abstract: We propose a simple and yet robust measure of tail neutrality. By this measure, hedge funds are more sensitive to market risk when the market experiences a substantial decline. This is also true when we consider a number of distinct hedge fund styles. This source of risk is not diversifiable, and for this reason funds-of-funds as portfolios of hedge funds concentrate tail risk exposure rather than mitigate this effect.

In today's uncertain market environment, the idea of investing in a fund immune from the day-to-day fluctuations in the market has a certain attraction. Indeed most hedge funds strategies generate returns that are reasonably uncorrelated with standard benchmarks. This leads many investors to believe that they are actually less risky than their active trading strategies would suggest. For many hedge funds this low correlation is illusory. Many active trading strategies that anticipate market movements will enter and leave the market with some frequency generating returns that are uncorrelated with benchmarks over the extended holding period of the average hedge fund investor. But this does not imply that they are low risk strategies, as in the kind of liquidity crisis that could prove fatal to the success of these trading schemes would cause the funds to fail just as the market is collapsing. This is of concern not only to investors but also to regulators as well. The bailout of LTCM in 1998 was occasioned by fears among regulators that liquidity problems at this fund could have a contagion effect spreading across the financial markets[1]. There is also the view among certain regulators that active trading by hedge funds can by its very nature induce liquidity crises. They point to the example of the Asian currency crisis of 1997[2]. On the other hand Boyson, Stahel and Stulz suggest that there is only very limited evidence that hedge funds taken as a whole have any role to play in financial contagion events. While of some comfort to those who fear long term consequences from the explosive growth of hedge funds and the role they may play in the financial system, these results do not exclude the possibility that individual funds might be adversely affected by financial crises.

Market neutral hedge strategies are in strong demand, though the true condition of market neutrality remains elusive to even the most well known hedge funds. Certain high profile market neutral managers were very market neutral… until they weren't. And in some cases, they were shown to be not-so-market-neutral in spectacular fashion. As generally understood by the meaning of the term, market neutral strategies generate returns that are uncorrelated with standard market benchmarks of performance. It is important to note that zero correlation is an outcome of a market neutral strategy; it does not define such a strategy. However, this distinction is often confused in the public mind, and today any strategy that generates returns which have no correlation with some stated benchmark over a given sample period is loosely called "market neutral".

[1] For a discussion of issues surrounding the failure of LTCM, see Lowenstein [2000]. A discussion of regulatory concern about hedge funds and contagion can be found in Boyson, Stahel and Stulz [2006]

[2] "We are now witnessing how damaging the trading of money can be to the economies of some countries and their currencies. It can be abused as no other trade can. Whole regions can be bankrupted by just a few people whose only objective is to enrich themselves and their rich clients" Mahathir bin Mohamad, [1997]. Dr. Mahathir's conclusion that hedge funds were responsible for the Asian currency crisis is challenged in Brown, Goetzmann and Park [2000].

Traditionally market neutral investing has been the domain of arbitrageurs, looking for small pricing discrepancies between financial instruments. The objective of market neutral funds is to profit without being exposed to the vagaries of the general market, that is, beta neutral. The arbitrage concept is founded on the belief that securities on each side of the transaction have a proven interrelationship. A profit is made when a trade is placed when there is a gap between the prices of these correlated securities with the expectation that the prices then converge to fair value. It is trading pricing discrepancies ahead of this eventual convergence that affords the investment opportunity, independent of market movements.

A different but related concept of market neutrality arises from the observations Loomis [1966] made about the original hedge fund organized by AW Jones. Jones' strategy was to take a long position in overvalued stocks financed in part by short positions taken in stocks perceived to be overvalued. This type of investing is now called dollar market neutrality, and Nicholas [2000] found it to be a common characteristic of all equity market neutral strategies. Because of institutional limitations on the nature and extent of short positions it is inevitable that such strategies have a long bias, and the beta of such strategies is typically of the order of about 0.2 [Fung and Hsieh 2004].

Market neutral funds are in high demand by institutional investors interested in minimizing financial risk traditionally associated with hedge fund investments, and a little over half of all hedge funds characterize themselves as Long/Short Equity funds and

Equity Market Neutral funds[3]. Patton [2004] argues that common definitions of market neutrality ignore the desires of risk averse investors. For instance, many institutional investors would be happy with a fund whose return was uncorrelated with the market at a time when the market performance is negative, but would prefer a positive correlation when the market rises in value. Yet recent work by Agarwal and Naik [2004] shows that many hedge fund strategies yield payoffs that are concave to benchmark. In other words, fund returns are most highly correlated with the market when the market falls in value. Patton [2004] argues for a new measure of "tail neutrality" which examines returns in the context of extreme events.

The purpose of this paper is to propose a simple and robust measure of tail neutrality. While hedge fund returns are not highly correlated with standard benchmarks, they are not tail neutral. This is particularly true of Long/Short strategies, the largest single style designation. Surprisingly, traditional market neutral strategies such as Event Driven and Convertible Arbitrage strategies are highly correlated with the S&P benchmark when the benchmark falls in value. Many institutional investors seek to minimize financial risk by investing in portfolios of hedge funds. These portfolios of funds are called funds-of-funds and have grown from 15 percent of all hedge funds in 2000 to 28 percent in 2005. The difficulty is that tail risk is not diversifiable, and funds-of-funds also fail the tail risk neutrality test.

[3] Of the 2781 hedge funds in the TASS universe of hedge funds (excluding funds-of-funds) in September 2005, 217 characterized themselves as Equity Market Neutral and 1196 were identified as Long/Short Equity

The paper is organized as follows. Section 1 briefly reviews approaches to understanding tail dependence. Section 3 describes the procedures of the study and compares their merits in a simulation study. Section 4 illustrates the application of our robust tail neutrality measure to the universe of hedge funds covered in the TASS database. Alternative benchmarks are examined in Section 5. Section 6 concludes.

1. Overview of Tail Methodologies

Hedge fund returns, like the returns to other financial asset classes, are not well described by multivariate normality. Negative skewness and excess kurtosis rule out simple linear market model representations of the CAPM[4]. They call into question the venerable Sharpe ratio, such a pervasive performance measure amongst hedge funds[5]. Heavy tails lead to 'unusually' large returns (both negative and positive) occurring with far greater frequency than normality would suggest. Episodes such as the LTCM crisis result in large negative returns in both funds and portfolios of funds, regardless of the claims that are made about market neutrality.

Since an understanding of portfolio risk requires an understanding of the dependence structure of the portfolio constituents, many new and interesting multivariate techniques dealing with higher order moments have been introduced into financial econometrics. The earliest development was the co-moment approach of Rubinstein (1973). Since many

[4] See for example, Rubinstein (1973) and Harvey and Siddique (2000)
[5] Indeed, the concave payout strategies documented among hedge funds in the work of Agarwal and Naik [2004] can be shown to lead to artificially high Sharpe ratios and significant downside risk potential (Weisman, [2002] and Goetzmann, Ingersoll, Spiegel and Welch [2004]).

of these approaches involve Taylor series expansions around expected return or the pricing kernel it is not clear how useful they might be in the context of extreme outcomes.

A more recent approach has been to use copulas[6], which are functions that fully describe the dependence structure of multivariate distributions without providing any information about the marginal distribution of returns on individual assets. This allows the dependence structure to be neatly decoupled from the security's univariate return characteristics. Conveniently, Sklar's theorem shows that there exists a unique copula if the marginal distributions are continuous. Even accepting that security returns are continuous, thereby ruling out jump processes or the extreme kinds of events that characterized the collapse of LTCM[7], there is no guarantee that the resulting copula conforms to the one or more of the parametric forms that are commonly used to characterize copulas.

Extreme Value Theory focuses solely on the tails of distributions, allowing the 'tails to speak for themselves'. Powerful limit theorems (which essentially analogs of the central limit theorems) describe the behavior of distributions in the tails without requiring strong parametric assumptions about the distribution of security returns. Coles, Heffernan and Tawn [1999] describe the bivariate techniques in detail and Poon, Rockinger and Tawn [2004] use these techniques to analyze the joint tail behavior of various international equity indices. Spitzer (2006) shows that past joint tail behavior between stocks and the

[6] For an introduction to the theory of copulas, see Joe [1997].
[7] For a description of the circumstances surrounding the fall of LTCM, see Lowenstein (2000)

overall market has strong explanatory power for the cross-section of future expected returns, in stark contrast to the poor predictive performance of overall market beta.

Unfortunately, such techniques are difficult to implement with hedge fund returns, since they are reported at a monthly frequency and have generally short time series. The large samples required to estimate co-moment, copulas or measures of limiting behavior simply don't exist[8], so our innovation is to exploit the cross-section. By aggregating, we can detect the extra dependence which would be indistinguishable from noise in the individual series.

The portfolio implications of increased dependence during extreme markets have been studied in the international portfolio choice literature. The home bias puzzle of investors investing more of their portfolio in domestic markets than mean-variance analysis would suggest is optimal. Das and Uppal (2004), Campbell and Kräussl (2005), Guidolin and Allan (2005) and others suggest that this is because correlation amongst international markets increases during crashes, causing diversification to fail precisely when investors need it most.

2 Data

[8] Boysen, Stahel and Stulz [2006] do have a daily series for hedge fund indices, but the component funds that are able to report daily returns are not likely to be representative of the broader industry. Getmansky, Lo and Makarov (2004) find that stale prices and illiquidity challenge the validity of high frequency hedge fund return calculations.

Hedge fund data is from the October 2005 TASS database. To be included in the sample, we require the fund be domiciled in the US and to have at least ten return observations after the fund was added to the database. While requiring a minimum number of observations will induce survivorship bias into the sample, it is unavoidable. To minimize such a bias, defunct funds from the TASS "graveyard" file are included and any fund returns that precede the funds addition to the database are discarded. TASS commenced adding defunct funds to the "graveyard" file in 1994 so we restrict our sample to returns from the 1994-2004 period.

TASS has eleven style designations: Funds-of-funds, Convertible Arbitrage, Dedicated Short Bias, Emerging Markets, Equity Market Neutral, Event Driven, Fixed Income Arbitrage, Global Macro, Long Short Equity, Managed Futures and Multi-strategy funds[9]. Since there is no reason to expect Multi-strategy funds to be homogenous, these funds are not examined as a separate style (although they are included when examining all funds together.)

[INSERT TABLE 1 ABOUT HERE]

The sample is described in Table 1 and broken out by style. Of the 1162 funds, by far the most numerous category is Long Short Equity (41.9%) followed by the Funds-of-funds (13.5%) and Event Driven Funds (11.5%). There are only twelve (1.0%) Dedicated Short Bias funds.

[9] These designations are self-reported by the funds and so can be subject to strategic self-misclassification (see Brown and Goetzmann (2003)).

The short return history is very evident with average sample length being 36 observations, with very little variation amongst categories. Our definition of a crash will need to be quite loose in order to get a decent number of observations. Consequently, we will use a return in the lowest decile as a crash return, throughout although this is not what we mean literally by a crash[10].

The other feature of the data not described in Table 1 is the increase in the number of funds over the sample period, so a fund-month chosen at random is more likely to have occurred towards the end of the sample.

For the market return, we use the return on the S&P 500 index. In Section 5, we consider the three-month LIBOR rate, the return on the Federal Reserve Dollar competitiveness index and the Lehman Brothers Aggregate Bond index.

3. Alternative measures of tail risk neutrality

Most investors associate the term "market neutrality" with funds whose returns are uncorrelated with standard benchmarks. The correlation coefficient is indeed a satisfactory measure of association where returns follow a Multivariate Normal distribution. This, however, is not the case for hedge funds. The simple correlation

[10] Spitzer [2006] shows that historical estimates gained from using a relatively loose definition, such as lowest 5% for daily equity returns, can have a great deal of explanatory power for the cross–section of equity returns when the subsequent market return is lower than anything previously recorded such as on Oct 19th, 1987.

coefficient cannot capture all of the possible degrees of association that may arise where returns are skewed or display significant kurtosis. In particular, it does not capture the possibility that while funds may be generally uncorrelated in their returns, they may become highly correlated in market crashes. For this reason, we need to consider alternative measures of tail risk neutrality.

The strictest measure of market neutrality has hedge fund returns literally independent of the returns on standard benchmarks. The classic approach to examining questions of this nature is to compare the joint frequency distribution to the theoretical distribution assuming independence. If we consider deciles of performance, we can compute a ten by ten table that records the frequency with which fund returns and benchmark returns fall between stated deciles. There is considerable cross sectional dispersion in the degree of leverage across funds. To control for the resulting cross-sectional differences in fund return variance, we define the fund return deciles specific to each fund. Thus, the returns of each fund are classified according to the deciles of just that fund, rather than the deciles of the aggregate fund return distribution. Under the null hypothesis of independence, the chance of falling into any bin should be equal since there is no relation between either series. This hypothesis can be tested using the standard Pearson Chi-Squared test statistic[11]

However, as we indicate before, the investor is not particularly interested in independence as a desirable attribute. The chief attraction of hedge fund neutrality is the

[11] Agresti (1990) p. 47 has a useful account of the history and application of this measure.

idea that funds can earn returns even when the benchmarks record very unsatisfactory returns. In other words, funds may be more or less correlated with the benchmark. We are interested to know whether correlation with the benchmark increases or decreases in crashes and other liquidity crises.

This can be addressed by considering just the number of observations that fall into the lowest decile for both fund and benchmark. If the returns are independent there should be one percent of the observations falling into this crash state. If returns on the fund and benchmark are bivariate Normal, this fraction will increase with the extent of return correlation. Fat tailed distributions such as the bivariate t with small degrees of freedom will show a greater frequency of crash state observations even when the correlation coefficient is zero. The relation between correlation and the frequency of crash state is presented in Figure 1. A simple procedure to detect excess tail dependence is to compare the actual frequency with the theoretical frequency given the observed fund benchmark correlation. This suggests a very simple binomial test for excess tail dependence.
First, collapse the 10x10 grid into four categories:

- LL for observations with both market and fund in the lower decile,
- WW for observations with neither market and fund in the lower decile,
- LW for observations with the fund but not the market in the lower decile,
- WL for observations with the market but not the fund in the lower decile.

and then compute the standard odds ratio ((LL * WW) / (LW * WL)) [12]. This can then be compared to the odds ratio implied by independence, bivariate Normality and bivariate t with low degrees of freedom given the expected frequencies depicted in Figure 1.

[INSERT FIGURE 1 ABOUT HERE]

Another approach is to fit logit regressions. Boyson, Stahel and Stulz (2006) regress a dummy equal to one when an hedge fund index has been in the lowest (or highest) 15% upon the market, a dummy for when the market is in the lowest (or highest) 15% and a number of other covariates. A significant positive coefficient on the market dummy is interpreted as evidence of contagion[13].

In order to evaluate each method, we conduct a simple simulation experiment. For each replication, a normally distributed excess market return, $R_{M,t}$ is simulated with monthly volatility of 4% corresponding to the monthly volatility of excess returns for the period of our sample. The next step is to simulate returns for 100 funds. Each fund has a beta of 0.32 and idiosyncratic volatility, $\varepsilon_{i,t}$, of 4.4%, which corresponds to the beta and idiosyncratic volatility of the average fund in the TASS database for the period of our

[12] Inference is based on the result that the log of this ratio distributed asymptotically normal with standard error equal to $\sqrt{1/WW + 1/LL + 1/LW + 1/WL}$ Agresti (1990) p. 54), suggests a continuity correction achieved by adding 0.5 to each cellcount

[13] . Boyson, Stahel and Stulz (2006) apply this procedure to daily observations of aggregated fund indices whereas in our empirical work we apply the technique to individual fund returns aggregated into style classifications.

sample. In order to parsimoniously model increased crash dependence[14], the beta of each fund is increased by some amount, β_{EXTRA} if the market return is in the lowest decile. The fund returns, $R_{i,t}$, are given by:

$$R_{i,t} = \begin{cases} \beta_i R_{M.t} + \varepsilon_{i,t} & R_{M,t} > F_{0.1}\left(R_{M,t}\right) \\ \left(\beta_i + \beta_{EXTRA}\right) R_{M.t} + \varepsilon_{i,t} & R_{M,t} \leq F_{0.1}\left(R_{M,t}\right) \end{cases}$$

where $F_{0.1}(R_{M,t})$ is the tenth percentile of the market return.

Under the null hypothesis of no tail dependence β_{EXTRA} is zero the joint distribution of fund returns and benchmark returns will be Multivariate Normal with a correlation coefficient of 0.28. For each replication, we calculate the frequency with which fund returns and benchmark returns fall into the lowest decile and compare it with the frequency that would be implied under the null hypothesis[15]. For completeness we also consider the frequency relative to what would be implied assuming independence. We then tally the results of the binomial and odds ratio tests against the null hypotheses of independence and against the hypothesis that the frequency of extreme events corresponds to that implied by bivariate Normality, counting how many times the test statistics are significant at the five percent level. In addition, we also tally the number of times the coefficient on the market dummy is significant and positive at the five percent level in a logit regression of the proportion of funds crashing in a month upon the market return and the crash dummy. The process is repeated five thousand times and Table 2 reports the power of the two tests for sample sizes of 40 observations (the average in our

[14] While we are abstracting from issues such as survivorship bias, more complicated forms of non-normality and lag dependence, the setup is sufficiently rich that the advantages of the cross-sectional approach are clear.

[15] Hedge fund returns are in fact fat tailed relative to the Normal distribution, and in the empirical results reported later in the paper we consider the fat tailed Bivariate Student t distribution.

TASS sample) and 120 observations (the longest history in the sample). β_{EXTRA} is set to zero for a baseline of no additional dependence as well as 0.05, 0.1, 0.2 and 0.5 for a spectrum of extra dependence ranging from mild to excessive.

[INSERT TABLE 2 ABOUT HERE]

Independence is easily rejected in all specifications, which is unsurprising given that each fund has a beta of 0.32.

For the binomial and odds ratio tests with $\beta_{EXTRA} = 0$ the null is true so the test should reject in five percent of cases, but the tests reject more frequently[16]. As β_{EXTRA} increases, power rises substantially but the odds ratio always outperforms the binomial test. Even though the data is drawn from a Normal distribution, it is surprising that the logit test is both misspecified and has limited power. The size of the test is incorrect as it rejects the null hypothesis in only a half to one percent of the simulations. In addition, the logit test has much lower power than either test.

4. Tail Neutrality of Hedge Funds

Before going on to the formal tests, most of the story can be told with very simple plots. Having constructed the ten-by-ten joint frequency distribution, we can plot the dependence by shading each bin according to the number of observations in that bin. The

[16] The fact that we reject too frequently when the null hypothesis is true may be a result of using the sample deciles rather than the true deciles to classify the observations.

colors vary smoothly from magenta for the bin with the most observations through to cyan for empty bins.

If fund returns were truly independent of market returns, the plot would be magenta since each bin would have the same number of observations. For a positive relation, the diagonal between the lower-left and upper-right will be darker. If the fund returns were negatively related to the market returns, the diagonal between the upper-left and lower-right corner would be darker.

[INSERT FIGURE 2 ABOUT HERE]

Figure 2a) plots the ranked returns for all hedge funds. The most immediate feature of the plot is the positive relation, however the key feature of the plot is that the modal outcome is the worst returns of the funds coinciding with the worst returns of the market (3.2% of the observations pairs (1,522 of 47,809)). Hedge funds are clearly not market neutral, no matter what definition of market neutrality is used.

[INSERT FIGURE 3 ABOUT HERE]

Figure 3 presents the plots for the true cell counts from a bivariate normal and a bivariate student t with three degrees of freedom. Each distribution has correlation equal that of the full sample. Each of the distributions has more dependence throughout the body of the distribution than the observed data, but neither has as high a proportion of observations in the joint lowest decile. The other stark contrast is the number of observations in the joint top decile, which is noticeably absent in the data.

While funds-of-funds can provide investors with access to funds that are otherwise closed to investors, another oft-touted advantage of funds-of-funds is their ability to diversify away much of the risk of investing in hedge funds. Figure 2b) demonstrates the important observation that tail risk is not diversifiable. If liquidity events or other market crises adversely affect all funds at the same time, then portfolios of funds will suffer at the same time that the individual fund components do poorly[17].

One possible explanation for these findings is that many of the funds in the sample suffered losses during the liquidity crisis that accompanied the collapse of LTCM. To investigate this hypothesis we excluded the month of LTCM's collapse. The pictures we obtained were visually indistinguishable from those obtained without the LTCM exclusion. We cannot attribute the results to the LTCM liquidity event.

The remaining panels of Figure 2 show similar dependence structures for Emerging Market funds, Event Driven funds and Long Short Equity funds. Not surprisingly, Dedicated Short Bias funds exhibit a negative relationship with the market and they exhibit their best returns when the market does worst. The overall dependence structure for Convertible Arbitrage and Equity Market Neutral funds is not clear, although the

[17] This is consistent with the results of Boyson, Stahel and Stulz (2006) who find that hedge fund returns are indeed correlated on the downside.

crash-crash outcome is again heavily represented. The remaining styles do not exhibit any clear market dependence structure.

[INSERT TABLE 3 ABOUT HERE]

Table 3 presents the results of the formal tests. As one would expect from the plots, independence can be rejected for all hedge funds combined, and each style group except for Fixed Income Arbitrage and Global Macro.

The binomial tests of independence in the joint lower decile are strongly rejected for the combined group of funds as well as the Funds-of-funds. In fact, most categories fail the test although Fixed Income Arbitrage is again independent. Despite being unable to reject independence over the full distribution, Global Macro funds crash more often during market crashes than we would expect by chance and Dedicated Short Bias, due to the predominantly short market position has a significantly lower probability. Interestingly, Managed Futures which failed the Chi-squared test shows no evidence of crash dependence. For the tests against correlated benchmarks, All Funds, the Funds-of-funds, Event Driven Funds and the Long-Short Equity all have more exposure to bivariate tail risk than we would observe under the most extreme assumption that the joint distribution of fund and benchmark returns corresponds to a Student t distribution with only three degrees of freedom.

Table 3 also presents the results of the odds ratio tests, which provide a convenient interpretation of the dependence. For the combined funds group, the odds that a fund crashes when the market crashes are five time the odds that the fund will crash otherwise. For the funds-of-funds, which have a lower overall beta than the combined group, the odds ratio is nearly eight. The conclusions drawn from the tests are identical to those drawn from the binomial tests.

There are two possible concerns. The first is that hedge funds often invest in illiquid securities resulting in a lag structure for dependencies. The procedures can be repeated using two-month returns to better (but not completely) capture these effects and the results are quantitatively and qualitatively the same. The second is that there is some other commonality to the categories which drives the results. To address this we repeat the exercises using the residuals from a regression of each funds return upon its own style benchmark. The pictures are the same if not starker and the formal tests yield similar results with the exception of the t benchmark tests which yield slightly different results.

Finally, Table 4 presents the results for the logit regressions. One convenient feature of the logit specification is that it allows us include lags of the market as additional covariates.

[INSERT TABLE 4 ABOUT HERE]

The simulation experiment reported in the previous Section suggests that this procedure lacks power to detect tail risk events. Even despite this fact, we find evidence consistent with the results reported in Table 3. Funds taken as a whole and funds-of-funds in particular show significant evidence of tail risk exposure. Not only is the probability of a significant fund return drawdown negatively associated with the return on the S&P 500 benchmark, but this probability is significantly increased when there is at the same time a significant drawdown evident in the benchmark returns. Of particular interest is the fact that there appears to be a lagged response to a market crash even for funds in general and event driven funds in particular. This result suggests that stale pricing may be a particular issue for this hedge fund style classification[18].

5. Alternative Benchmarks

Hedge funds also face other sources of risk. We consider three additional risks – bond market risk, LIBOR risk and foreign exchange risk.

Figure 5 presents the dependence plots for hedge fund returns and the Lehman Brothers Aggregate Bond Index. For all funds combined there is very little to note, however the Dedicated Short Bias, Equity Market Neutral, Global Macro and Managed Futures funds all exhibit their worst returns when the bond market crashes. Fixed Income Arbitrage funds do have bad returns when the bond market crashes, but not their worst. The formal tests in Table 5 confirm that these effects are significant against the normal benchmark, but not against the t benchmark.

[18] For a discussion of the stale pricing effect in hedge fund returns see .Getmansky, Lo and Makarov (2004)

[INSERT FIGURE 5 AND TABLE 5 ABOUT HERE]

Fund dependence on foreign exchange returns are plotted in Figure 6. Overall, funds have their best returns when the dollar drops and this effect is most pronounced in the Event Driven, Global Macro and Long Short Equity fund styles. Because many funds are exposed to this factor, the effect is concentrated in the Fund of Funds classification. Emerging market funds have their best returns when the dollar falls. These funds are most definitely not neutral to foreign exchange exposure.

[INSERT FIGURE 6 AND TABLE 6 ABOUT HERE]

Finally, Figure 7 presents dependence plots for the one month holding period return on three month LIBOR. Despite their low or negative correlations with this return, Convertible Arbitrage and Fixed Income Arbitrage funds get caught by the tail and perform very poorly when the LIBOR return is lowest. On the other hand, the Emerging Markets funds do particularly well when the LIBOR return is particularly high consistent with the view that LIBOR is a significant factor in emerging market returns.

[INSERT FIGURE 7 AND TABLE 7 ABOUT HERE]

Conclusion

Most market practitioners understand that the heady claims of market neutrality are descriptively inaccurate for hedge funds. All hedge fund styles with the possible exception of fixed income arbitrage are significantly correlated with the S&P 500 benchmark. Even funds that describe themselves as equity market neutral have a significant correlation with the S&P 500 benchmark. This perhaps explains why it is that the term "market neutrality" is going out of fashion and is being replaced by the more neutral term "absolute return" to describe what it is that hedge funds do.

In economic terms the correlations are small. Does this provide comfort for those investors who look to hedge funds to provide haven from the storm induced by a prospective market collapse? Not necessarily. On the basis of a simple and relatively robust measure of tail risk exposure, we find that hedge funds are more sensitive to market risk when the market declines substantially. This also follows where we consider particular styles of hedge fund management. There is also evidence of a lagged response to a market crash, consistent with evidence that stale prices may have a measurable impact on hedge fund returns.

One of the important attributes of tail risk exposure is that this risk is not diversifiable. If the market exposure of funds as a whole increase when the market collapses, then portfolios of funds will share this attribute. There are many good reasons to invest in a funds-of-funds vehicle, but diversification to avoid tail risk exposure is not one of them. Indeed, our findings are that if anything, funds-of-funds concentrate rather than dissipate tail risk exposure.

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Table 1
Sample Description

Funds are taken from the TASS database with returns from 1995 to 2004, including funds that have ceased reporting. To be included in the sample, a fund must be domiciled in the USA, report returns monthly and have at least ten actual returns following addition to the database. Returns prior to addition to the database are discarded.

	Number of Funds	Funds Ceased Reporting	Average Obs. per fund	Min. Obs.	Max. Obs.
All funds	1162	488	35.99	10	119
Funds-of-funds	157	50	36.86	10	117
Convertible Arbitrage	48	17	38.21	12	109
Dedicated Short Bias	12	6	43.42	11	82
Emerging Markets	25	17	48.64	12	108
Equity Market Neutral	70	32	36.79	10	108
Event Driven	131	48	39.66	10	111
Fixed Income Arbitrage	44	16	34.05	10	96
Global Macro	41	18	31.44	11	109
Long Short Equity	487	219	35.11	10	119
Managed Futures	104	45	32.65	11	89

Table 2
Specification and Power of Tests to Detect Increased Dependence During Crashes

This table reports the proportion of five thousand simulations in which extra crash dependence is detected at the five percent level. For each replication, a normally distributed excess market return is simulated with mean 0 and volatility 4% and a sample of either 40 or 120 observations. 100 funds are then simulated each with beta of 0.32 and idiosyncratic volatility of 4.4%. For observations when the market return is in its lowest decile, each funds beta is increased by β_{EXTRA}. The number of observations in the lowest decile of both the fund and the market is tested against benchmarks of independence, bivariate normality (with beta of 0.32) or Bivariate Student t (with beta of 0.32 and 3 degrees of freedom) using binomial tests. These tests are repeated using the exact odds ratio test. For the logit tests, the proportion of funds in the lowest decile is regressed upon the market return and a dummy for the market being in the lowest decile. Reported numbers for all tests are the proportion of replications in which extra dependence is detected (size when $\beta_{EXTRA} = 0$ against a normal benchmark or any specification against independence, power in the other cases).

Panel A. 40 observations per fund

	Binomial		Odds Ratio		Logit
	Independence	Normal	Independence	Normal	
$\beta_{EXTRA} = 0$	0.9996	0.0676	0.9996	0.0894	0.0116
$\beta_{EXTRA} = 0.05$	0.9998	0.2068	1	0.2592	0.0676
$\beta_{EXTRA} = 0.1$	1	0.444	1	0.502	0.1956
$\beta_{EXTRA} = 0.2$	1	0.8214	1	0.8484	0.6708
$\beta_{EXTRA} = 0.5$	1	0.9978	1	0.9984	0.9986

Panel A. 120 observations per fund

	Binomial		Odds Ratio		Logit
	Independence	Normal	Independence	Normal	
$\beta_{EXTRA} = 0$	1	0.0714	1	0.1012	0.0056
$\beta_{EXTRA} = 0.05$	1	0.4228	1	0.4944	0.0968
$\beta_{EXTRA} = 0.1$	1	0.8068	1	0.8556	0.4614
$\beta_{EXTRA} = 0.2$	1	0.9966	1	0.9984	0.9844
$\beta_{EXTRA} = 0.5$	1	1	1	1	1

Table 3
Tests of Dependency Among Hedge Fund Returns and Market Returns

The returns of each fund with more than ten observations are converted to percentiles as are corresponding returns on the S&P 500 index. The returns are then aggregated (either across all funds or funds within a particular style) and binned into a ten-by-ten grid. Reported Chi-squared numbers are the results of a test of independence using the full sample. Binomial Crash considers just the proportion of observations that fall into the lowest decile of both fund and market returns. The p-value (ind) is from a binomial test of local independence. The p-value(N) and the p-value (t) uses the proportion of crash events implied by a bivariate Normal or t distribution (with three degrees of freedom) and correlation equal to the sample correlation given in the first column of the table. The Odds Ratio test gives similar results assuming that the sample log odds ratio is distributed asymptotically as Normal with mean implied by the independence, Normal or t model and standard error given as the square root of the sum of reciprocal cell counts. The correlations with the S&P500 benchmark are provided with asterisks indicating significance at the one percent level. Data is monthly from 1995 through 2004.

	Correlation with benchmark	**Chi-Squared**		**Binomial Crash**				**Odds ratio test**			
		Test Stat	p-value	Proportions	p-value (ind)	p-value (N)	p-value (t)	Odds ratio	p-value (ind)	p-value (N)	p-value (t)
All Funds	0.28**	7249.302	0	1486/47809	0	0	0	5.439	0	0	0
Funds-of-funds	0.14**	1855.643	0	261/7090	0	0	0	7.712	0	0	0
Convertible Arbitrage	0.09**	302.940	0	37/1948	0	0.033	0.840	2.386	0	0.044	0.945
Dedicated Short Bias	-0.91**	477.353	0	0/585	0.997	0.112	0.838	0.067	0.985	0.570	0.991
Emerging Markets	0.66**	484.973	0	49/1242	0	0.031	0.394	8.997	0	0.007	0.371
Equity Market Neutral	0.02	181.225	0	48/2938	0.001	0.006	0.893	1.917	0.001	0.005	0.942
Event Driven	0.20**	1069.364	0	219/5703	0	0	0	8.478	0	0	0
Fixed Income Arbitrage	0.01	79.945	0.920	16/1559	0.395	0.480	0.995	1.057	0.456	0.550	1
Global Macro	0.08	138.038	0.006	25/1374	0.004	0.034	0.752	2.247	0.002	0.024	0.785
Long Short Equity	0.50**	5644.088	0	747/20276	0	0	0.006	7.728	0	0	0
Managed Futures	-0.11**	316.004	0	36/3521	0.563	0.127	0.999	1.038	0.448	0.075	1

Table 4
Cross-Sectional Fund Crash Probabilities

This table gives logit regression results of the number of funds that experience returns in the lower 10% of their return history in any given month. Data is monthly from 1995 through 2004. The market return used in this logit regression is the value weighted CRSP market in excess of the one month Treasury Bill return. The t-stats are in parenthesis.

	All funds	Funds-of-funds	Convertible Arbitrage	Dedicated Short Bias	Emerging Markets	Equity Market Neutral	Event Driven	Fixed Income Arbitrage	Global Macro	Long Short Equity	Managed Futures
Intercept	-2.39	-2.52	-2.29	-3.44	-2.74	-2.19	-2.58	-2.35	-2.15	-2.50	-2.06
	(-112.10)	(-41.95)	(-23.19)	(-10.06)	(-17.81)	(-27.05)	(-40.00)	(-20.24)	(-18.87)	(-71.02)	(-30.88)
Market Return	-10.70	-12.36	-2.73	39.04	-21.00	-3.77	-9.67	3.67	-2.02	-18.77	-2.80
	(-20.33)	(-8.18)	(-1.12)	(6.27)	(-6.32)	(-1.94)	(-6.35)	(1.41)	(-0.73)	(-20.77)	(-1.63)
Lagged Market Return	-3.56	-6.46	-8.56	2.23	-1.44	-1.99	-7.47	-0.48	-2.46	-1.60	-4.52
	(-6.95)	(-4.42)	(-3.52)	(0.50)	(-0.47)	(-1.04)	(-4.95)	(-0.19)	(-0.90)	(-1.93)	(-2.71)
Market Crash Dummy	0.38	0.71	0.50	2.21	0.34	0.08	0.65	0.54	-0.21	0.03	-0.97
	(5.93)	(4.04)	(1.51)	(1.74)	(0.97)	(0.30)	(3.54)	(1.44)	(-0.48)	(0.29)	(-3.04)
Lagged Market Crash Dummy	0.32	0.35	-0.03	-0.04	0.36	0.11	0.56	0.53	0.28	0.34	0.07
	(5.04)	(1.99)	(-0.09)	(-0.06)	(0.91)	(0.42)	(3.16)	(1.50)	(0.68)	(3.35)	(0.27)
McFadden's Pseudo-R^2	0.079	0.141	0.039	0.208	0.209	0.009	0.133	0.010	0.005	0.132	0.009

Table 5
Tests of Dependency Among Hedge Fund Returns and Bond Market Returns

The returns of each fund with more than ten observations are converted to percentiles as are corresponding returns on the Lehman Brothers aggregate bond index. The returns are then aggregated (either across all funds or funds within a particular style) and binned into a ten-by-ten grid. Reported Chi-squared numbers are the results of a test of independence using the full sample. Binomial Crash considers just the proportion of observations that fall into the lowest decile of both fund and market returns. The p-value (ind) is from a binomial test of local independence. The p-value(N) and the p-value (t) uses the proportion of crash events implied by a bivariate Normal or t distribution (with three degrees of freedom) and correlation equal to the sample correlation given in the first column of the table. The Odds Ratio test gives similar results assuming that the sample log odds ratio is distributed asymptotically as Normal with mean implied by the independence, Normal or t model and standard error given as the square root of the sum of reciprocal cell counts. The correlations with the Lehman Brothers benchmark are provided with asterisks indicating significance at the one percent level. Data is monthly from 1995 through 2004.

	Correlation with benchmark	**Chi-Squared**		**Binomial Crash**				**Odds ratio test**			
		Test Stat	p-value	Proportions	p-value (ind)	p-value (N)	p-value (t)	Odds ratio	p-value (ind)	p-value (N)	p-value (t)
All Funds	-0.01	1187.994	0	608/47809	0	0	1	1.357	0	0	1
Funds-of-funds	0.05**	431.201	0	96/7090	0.002	0.068	1	1.479	0.001	0.066	1
Convertible Arbitrage	0.04	205.197	0	18/1948	0.514	0.699	1	0.927	0.655	0.830	1
Dedicated Short Bias	0.14**	143.098	0.002	14/585	0.001	0.029	0.384	3.444	0.001	0.040	0.467
Emerging Markets	-0.11**	125.518	0.037	5/1242	0.986	0.857	1	0.383	0.997	0.937	1
Equity Market Neutral	0.04	111.417	0.185	49/2938	0	0.004	0.867	1.973	0	0.003	0.920
Event Driven	-0.03	206.969	0	45/5703	0.969	0.871	1	0.758	0.969	0.854	1
Fixed Income Arbitrage	0.04	156.726	0	27/1559	0.003	0.014	0.714	2.091	0.004	0.017	0.802
Global Macro	0.11**	135.327	0.009	30/1374	0	0.011	0.560	2.956	0	0.006	0.544
Long Short Equity	-0.07**	1082.428	0	220/20276	0.159	0.000	1	1.109	0.117	0	1
Managed Futures	0.19**	498.243	0	87/3521	0	0.001	0.720	3.601	0	0	0.628

Table 6
Tests of Dependency Among Hedge Fund Returns and USD Returns

The returns of each fund with more than ten observations are converted to percentiles as are corresponding returns on the Federal Reserve Dollar Competitiveness index. The returns are then aggregated (either across all funds or funds within a particular style) and binned into a ten-by-ten grid. Reported Chi-squared numbers are the results of a test of independence using the full sample. Binomial Crash considers just the proportion of observations that fall into the lowest decile of both fund and market returns. The p-value (ind) is from a binomial test of local independence. The p-value(N) and the p-value (t) uses the proportion of crash events implied by a bivariate Normal or t distribution (with three degrees of freedom) and correlation equal to the sample correlation given in the first column of the table. The Odds Ratio test gives similar results assuming that the sample log odds ratio is distributed asymptotically as Normal with mean implied by the independence, Normal or t model and standard error given as the square root of the sum of reciprocal cell counts. The correlations with the USD benchmark are provided with asterisks indicating significance at the one percent level. Data is monthly from 1995 through 2004.

	Correlation with benchmark	**Chi-Squared**		**Binomial Crash**				**Odds ratio test**			
		Test Stat	p-value	Proportions	p-value (ind)	p-value (N)	p-value (t)	Odds ratio	p-value (ind)	p-value (N)	p-value (t)
All Funds	-0.11**	1660.817	0	341/47809	1	0.488	1	0.668	1	0.353	1
Funds-of-funds	-0.12**	751.608	0	53/7090	0.983	0.166	1	0.711	0.987	0.193	1
Convertible Arbitrage	-0.10**	202.487	0	16/1948	0.695	0.213	0.993	0.808	0.796	0.312	1
Dedicated Short Bias	0.20**	126.573	0.032	17/585	0	0.012	0.234	4.802	0	0.012	0.258
Emerging Markets	-0.24**	216.992	0	8/1242	0.881	0.083	0.934	0.625	0.872	0.148	0.981
Equity Market Neutral	-0.04	120.805	0.067	26/2938	0.723	0.441	1	0.874	0.753	0.459	1
Event Driven	-0.12**	341.077	0	49/5703	0.904	0.064	1	0.838	0.855	0.044	1
Fixed Income Arbitrage	-0.05	119.866	0.075	18/1559	0.225	0.086	0.935	1.221	0.277	0.114	0.981
Global Macro	-0.09**	96.640	0.548	14/1374	0.479	0.121	0.944	1.051	0.475	0.127	0.977
Long Short Equity	-0.12**	879.158	0	107/20276	1	0.996	1	0.476	1	0.998	1
Managed Futures	-0.12**	426.553	0	22/3521	0.996	0.695	1	0.584	0.994	0.622	1

Table 7
Tests of Dependency Among Hedge Fund Returns and Three Month LIBOR Returns

The returns of each fund with more than ten observations are converted to percentiles as are corresponding one month return on three month LIBOR paper. The returns are then aggregated (either across all funds or funds within a particular style) and binned into a ten-by-ten grid. Reported Chi-squared numbers are the results of a test of independence using the full sample. Binomial Crash considers just the proportion of observations that fall into the lowest decile of both fund and market returns. The p-value (ind) is from a binomial test of local independence. The p-value(N) and the p-value (t) uses the proportion of crash events implied by a bivariate Normal or t distribution (with three degrees of freedom) and correlation equal to the sample correlation given in the first column of the table. The Odds Ratio test gives similar results assuming that the sample log odds ratio is distributed asymptotically as Normal with mean implied by the independence, Normal or t model and standard error given as the square root of the sum of reciprocal cell counts. The correlations with the benchmark are provided with asterisks indicating significance at the one percent level. Data is monthly from 1995 through 2004.

	Correlation with benchmark	**Chi-Squared**		**Binomial Crash**				**Odds ratio test**			
		Test Stat	p-value	Proportions	p-value (ind)	p-value (N)	p-value (t)	Odds ratio	p-value (ind)	p-value (N)	p-value (t)
All Funds	0.00	371.371	0	324/47809	1	1	1	0.630	1	1	1
Funds-of-funds	0.01	280.190	0	29/7090	1	1	1	0.363	1	1	1
Convertible Arbitrage	0.00	159.371	0	43/1948	0	0	0.074	3.001	0	0	0.082
Dedicated Short Bias	0.07	111.498	0.184	12/585	0.006	0.031	0.432	2.711	0.012	0.051	0.533
Emerging Markets	-0.17**	138.542	0.005	4/1242	0.995	0.823	1	0.308	0.999	0.921	1
Equity Market Neutral	0.07**	115.513	0.123	35/2938	0.148	0.567	1	1.259	0.125	0.589	1
Event Driven	-0.04**	155.571	0	27/5703	1	1	1	0.427	1	1	1
Fixed Income Arbitrage	-0.05	126.673	0.032	39/1559	0	0	0.007	3.683	0	0	0.004
Global Macro	-0.03	90.083	0.728	10/1374	0.849	0.756	0.999	0.711	0.886	0.798	1
Long Short Equity	0.00	434.344	0	77/20276	1	1	1	0.332	1	1	1
Managed Futures	-0.02	245.892	0	37/3521	0.525	0.399	1	1.074	0.375	0.256	1

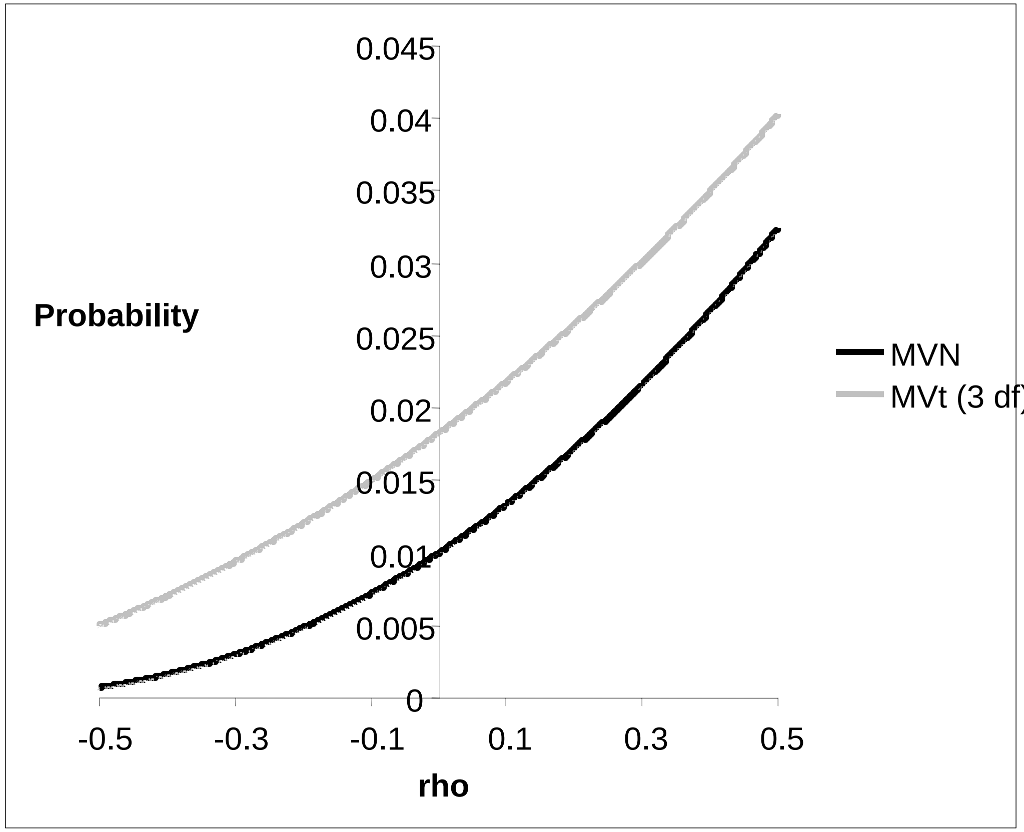
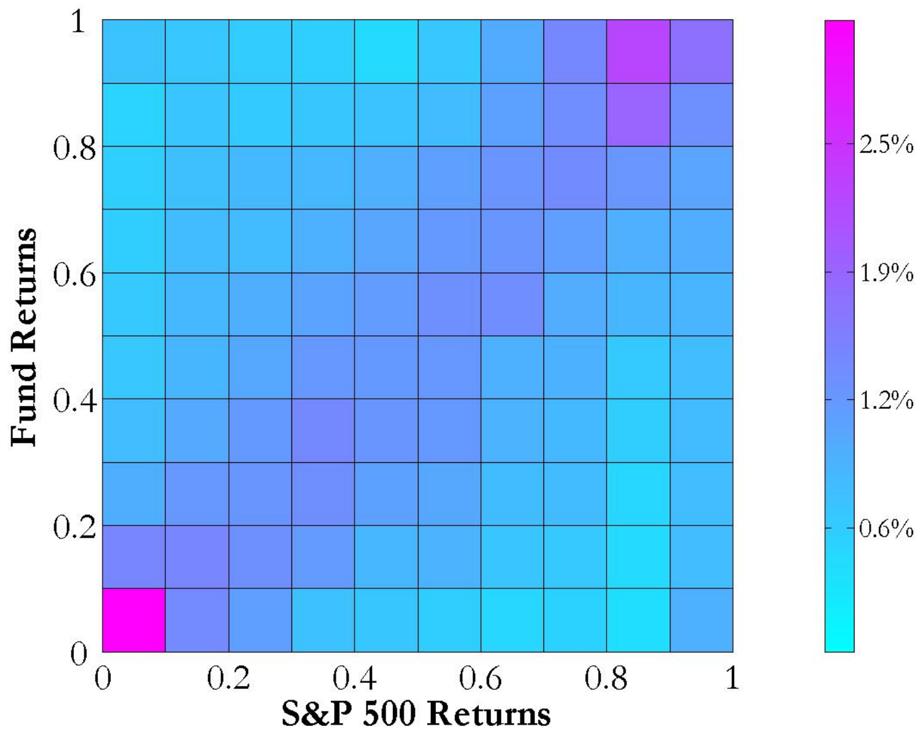
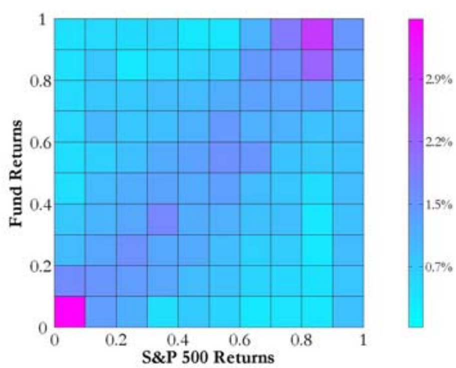


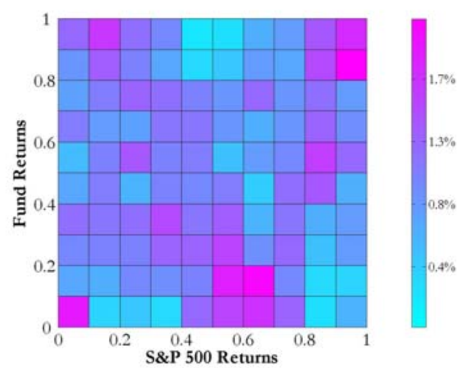
Figure 1 Probability of falling into lower decile for fund and benchmark when returns are distributed as Multivariate Normal and Multivariate t (3 d.f.)



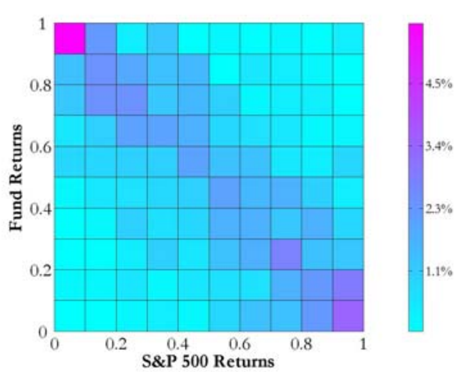
a) All Hedge Funds (ρ = 0.24, β = 0.28)



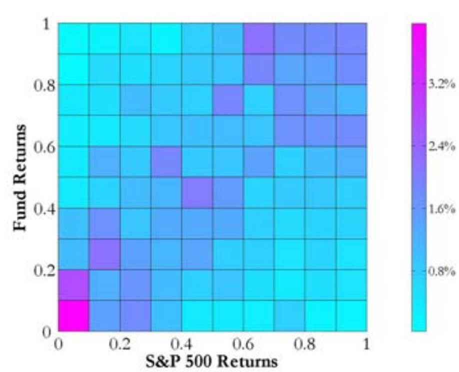
b) Funds-of-funds (ρ = 0.22, β = 0.14)



c) Convertible Arbitrage (ρ = 0.14, β = 0.09)

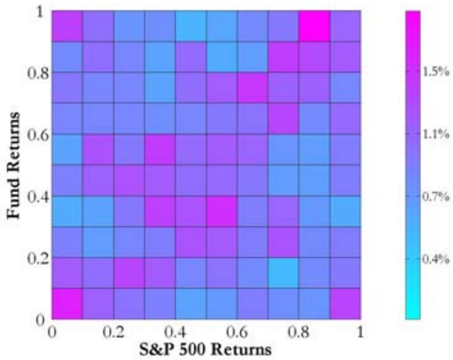


d) Dedicated Short Bias (ρ = -0.61, β = -0.91)

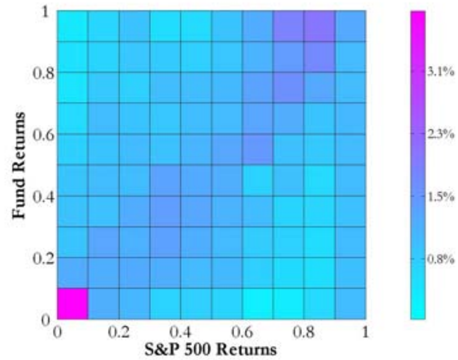


e) Emerging Market (ρ = 0.46, β = 0.66)

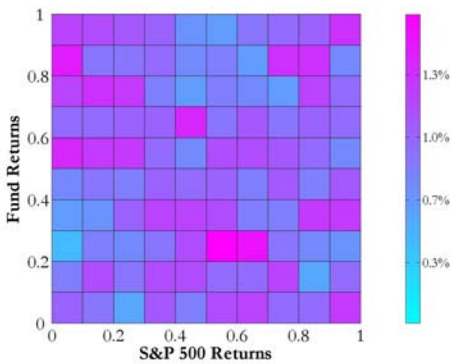
Figure 2. Cross-Sectional Rank-Rank Plots



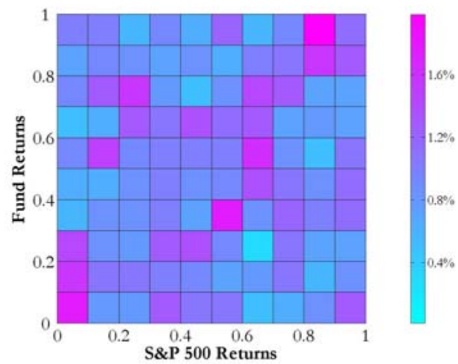
f) Equity Market Neutral ($\rho = 0.04$, $\beta = 0.02$)



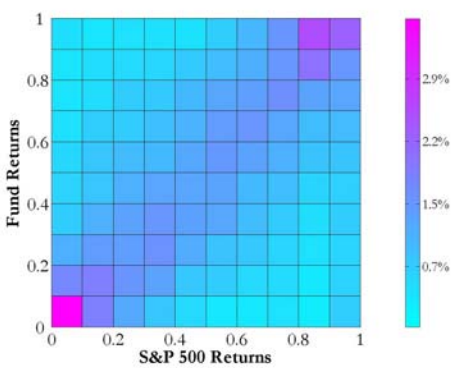
g) Event Driven ($\rho = 0.23$, $\beta = 0.20$)



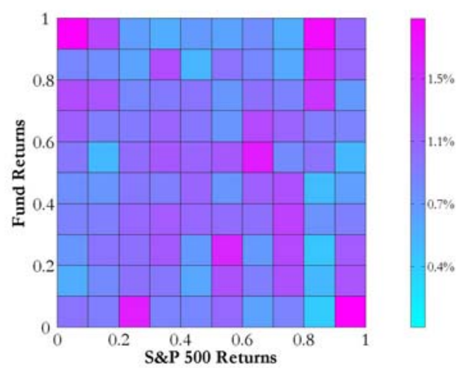
h) Fixed Income Arbitrage ($\rho = 0.02$, $\beta = 0.01$)



i) Global Macro ($\rho = 0.07$, $\beta = 0.08$)

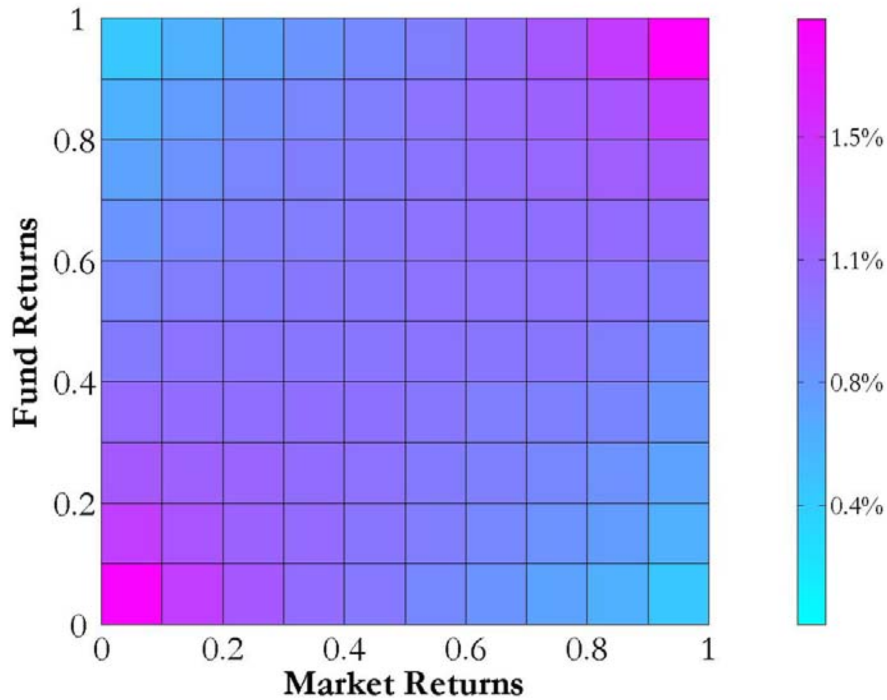


j) Long Short Equity ($\rho = 0.37$, $\beta = 0.50$)

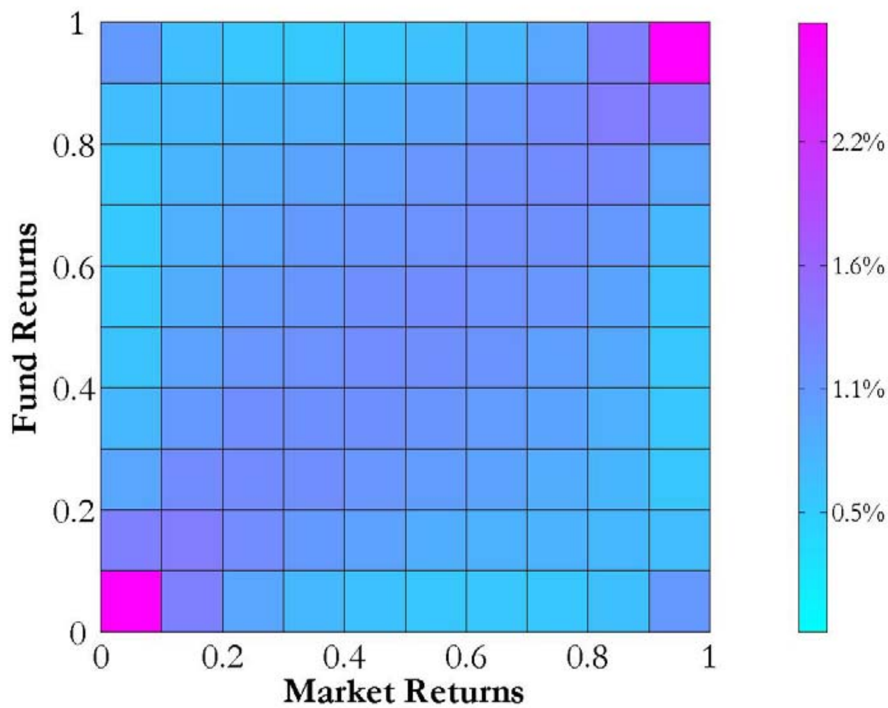


k) Managed Futures ($\rho = -0.07$, $\beta = -0.11$)

Figure 2. Cross-Sectional Rank-Rank Plots (continued)

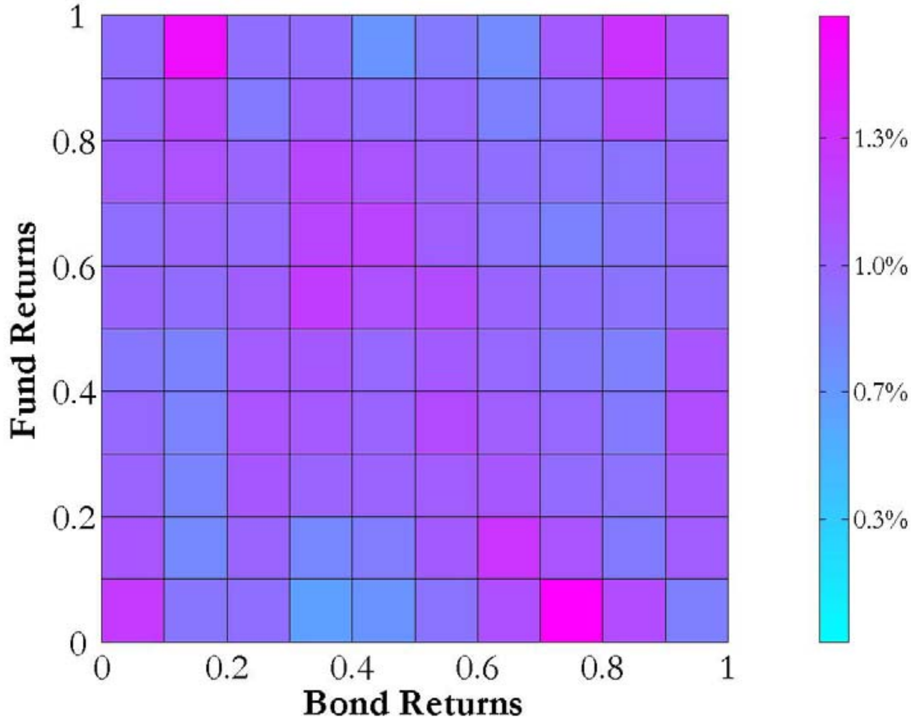


a) Bivariate Normality

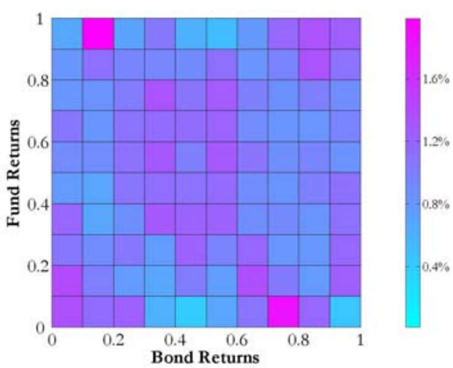


b) Bivariate Student t with 3 df

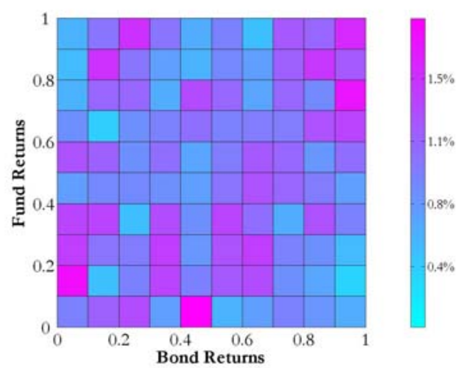
Figure 3. Theoretical Rank-Rank Plots With Correlation Equal to Sample



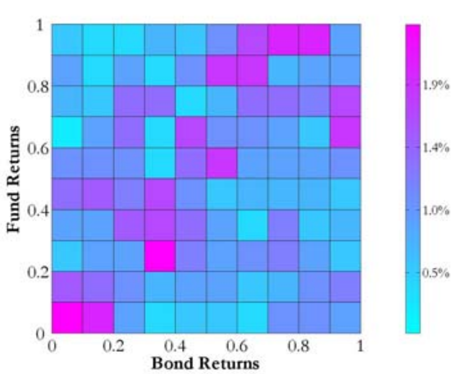
a) All Hedge Funds (ρ = -0.01, β = -0.04)



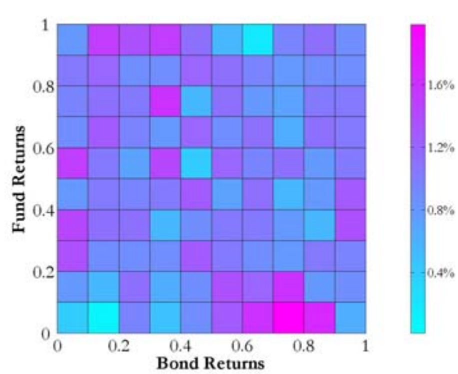
b) Funds-of-funds (ρ = 0.05, β = 0.12)



c) Convertible Arbitrage (ρ = 0.04, β = 0.08)

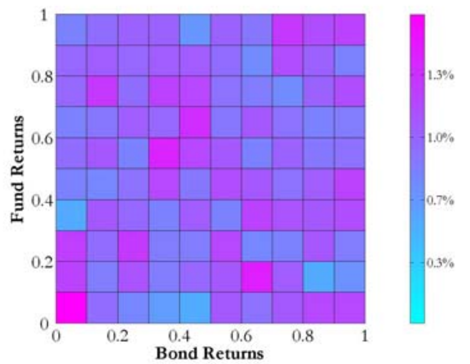


d) Dedicated Short Bias (ρ = 0.14, β = 0.83)

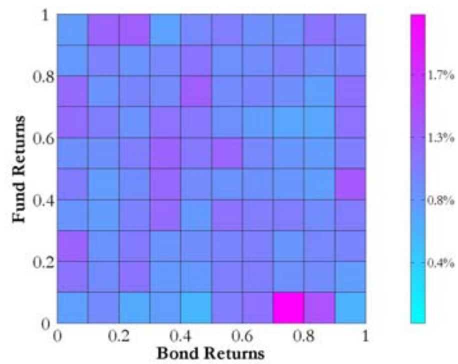


e) Emerging Markets (ρ = -0.11, β = -0.67)

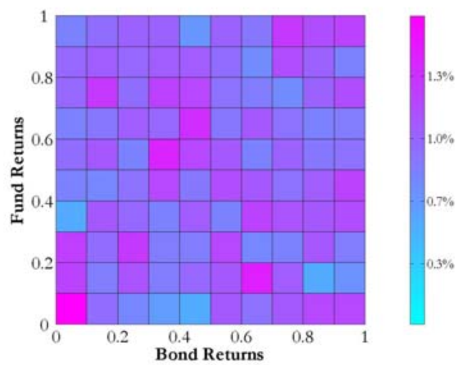
Figure 4. Cross-Sectional Rank-Rank Plots of Fund Returns and Bond Market Returns



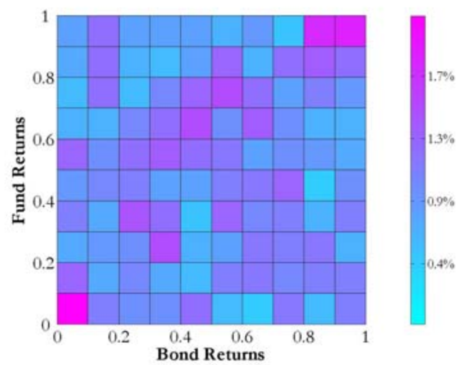
f) Equity Market Neutral (ρ = 0.04, β = 0.08)



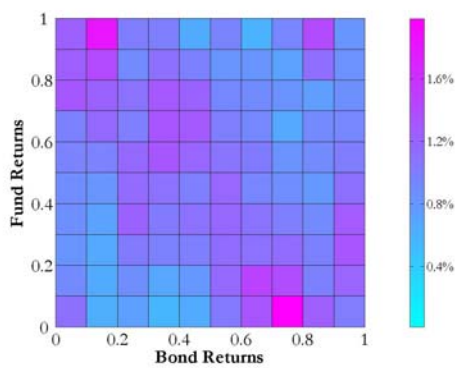
g) Event Driven (ρ = -0.03, β = -0.10)



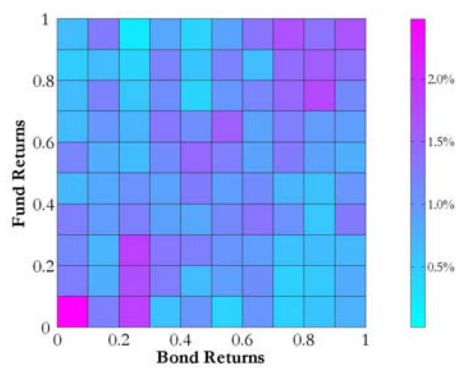
g) Fixed Income Arbitrage (ρ = 0.04, β = 0.10)



h) Global Macro (ρ = 0.11, β = 0.43)

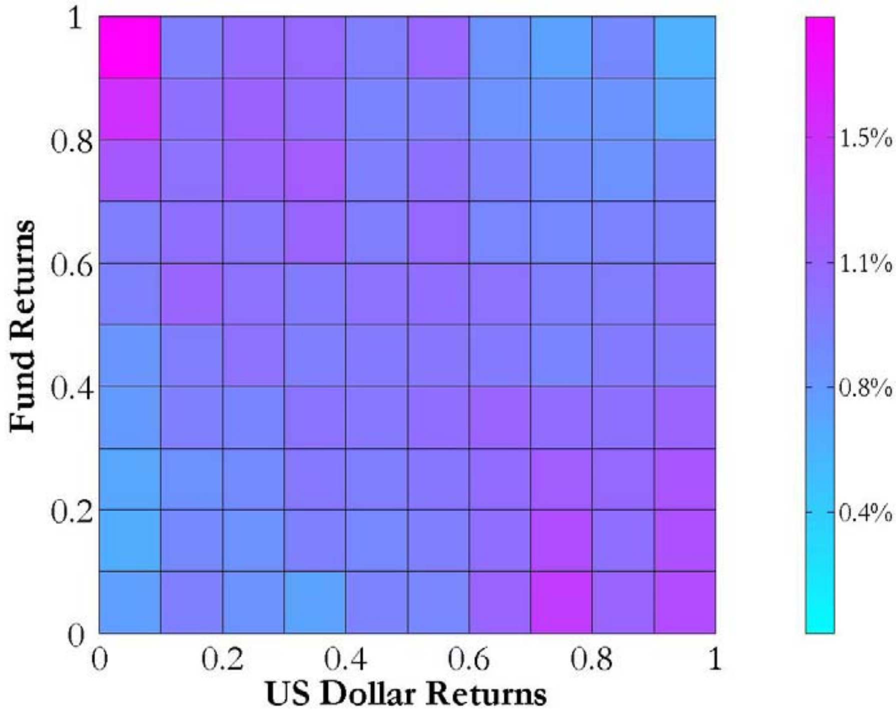


h) Long Short Equity (ρ = -0.07, β = -0.34)

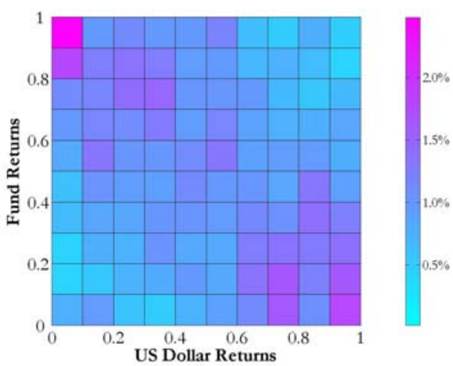


i) Managed Futures (ρ = 0.19, β = 1.03)

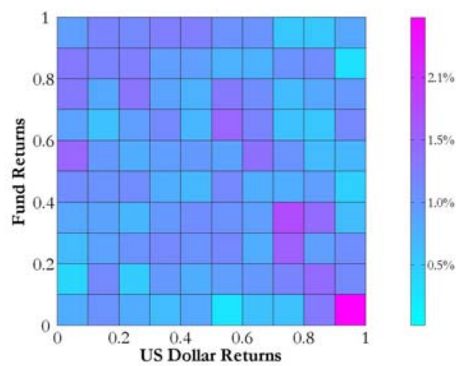
Figure 4. Cross-Sectional Rank-Rank Plots of Fund Returns and Bond Market Returns (continued)



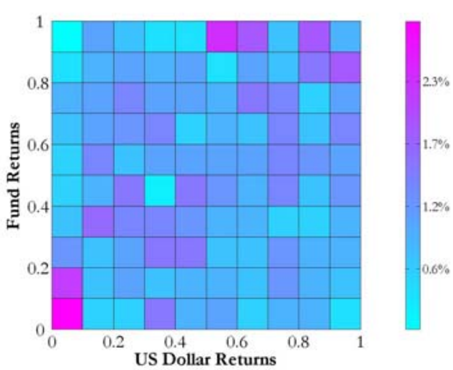
b) All Hedge Funds (ρ = -0.11, β = -0.49)



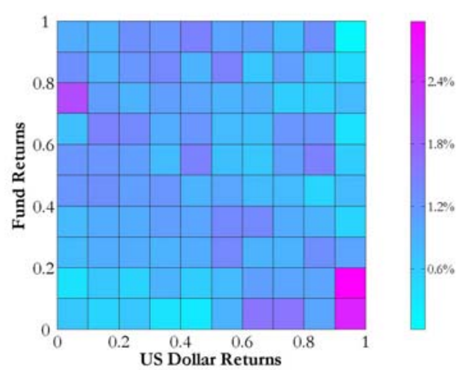
b) Funds-of-funds (ρ = -0.12, β = -0.29)



c) Convertible Arbitrage (ρ = -0.10, β = -0.13)



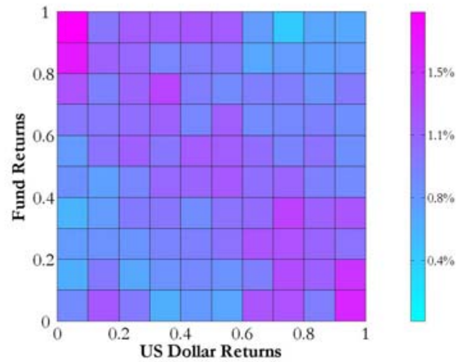
d) Dedicated Short Bias (ρ = 0.20, β = 1.20)



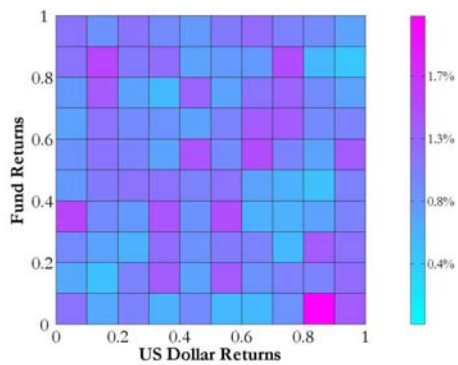
e) Emerging Markets (ρ = -0.24, β = -1.48)

Figure 5. Cross-Sectional Rank-Rank Plots of Fund Returns and USD Returns

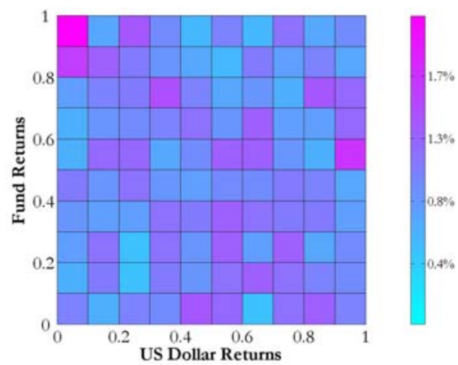
f) Equity Market Neutral (ρ = -0.04, β = -0.12)



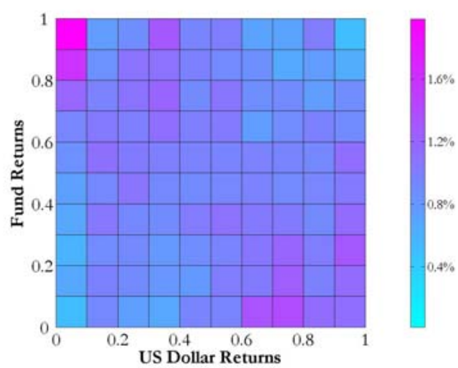
g) Event Driven (ρ = -0.12, β = -0.42)



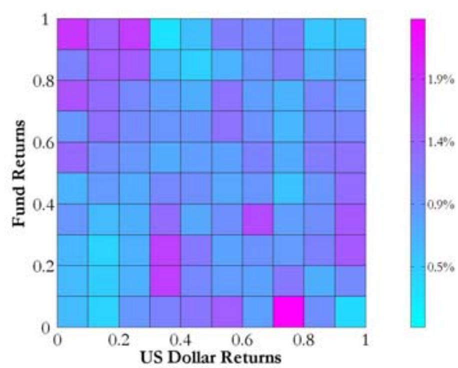
g) Fixed Income Arbitrage (ρ = -0.05, β = -0.13)



h) Global Macro (ρ = -0.09, β = -0.41)

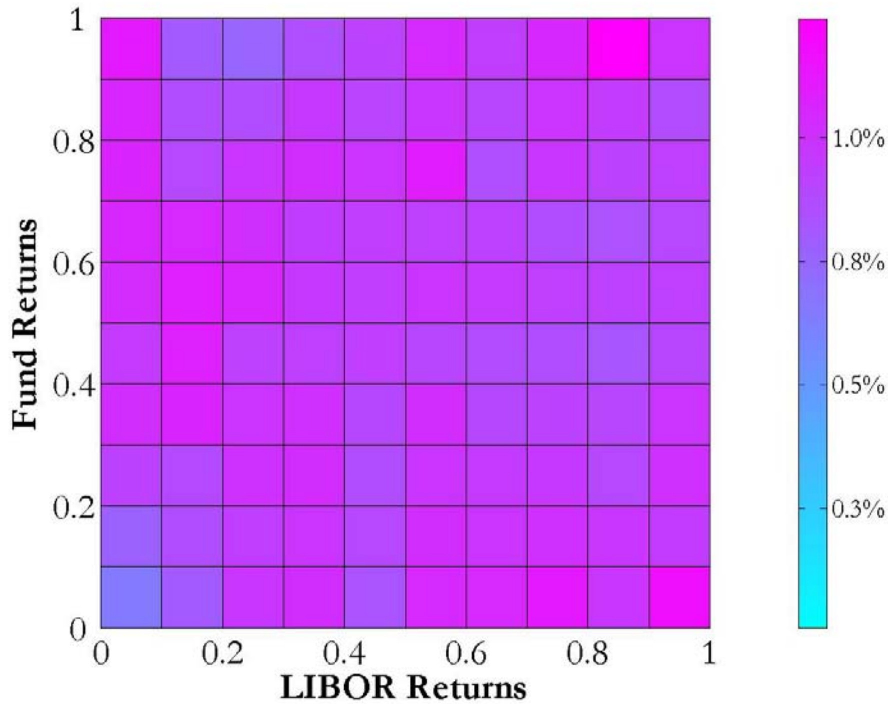


h) Long Short Equity (ρ = -0.12, β = -0.67)

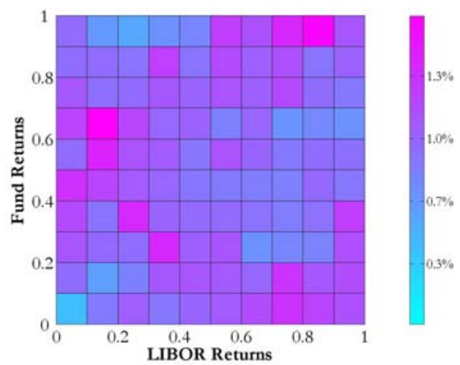


i) Managed Futures (ρ = -0.12, β = -0.73)

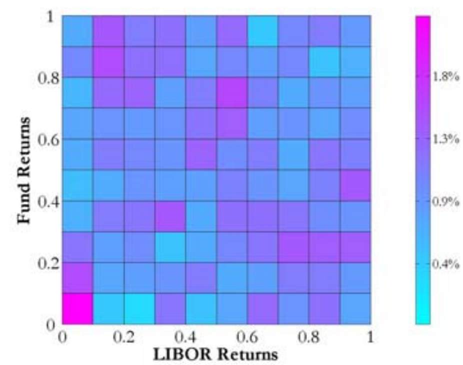
Figure 5. Cross-Sectional Rank-Rank Plots of Fund Returns and USD Returns (continued)



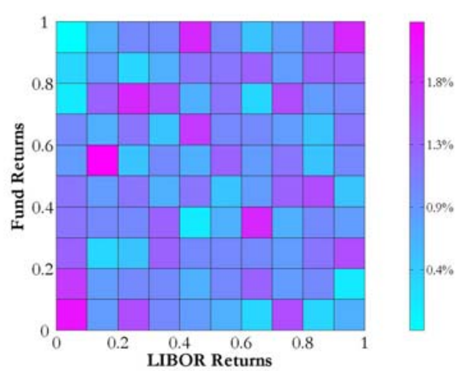
c)   All Hedge Funds (ρ = 0.00, β = 0.00)



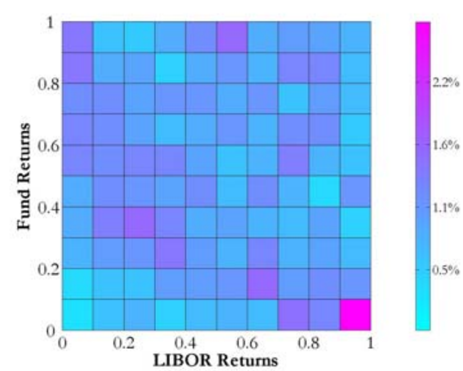
b) Funds-of-funds (ρ = 0.01, β = 0.00)



c) Convertible Arbitrage (ρ = 0.00, β = 0.00)

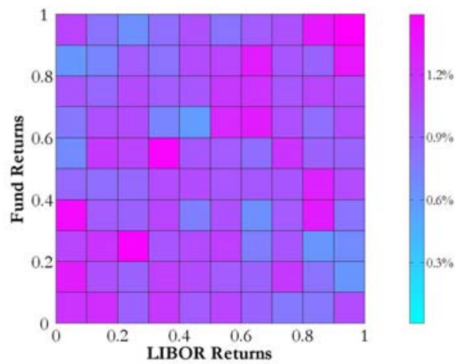


d) Dedicated Short Bias (ρ = 0.07, β = 0.06)

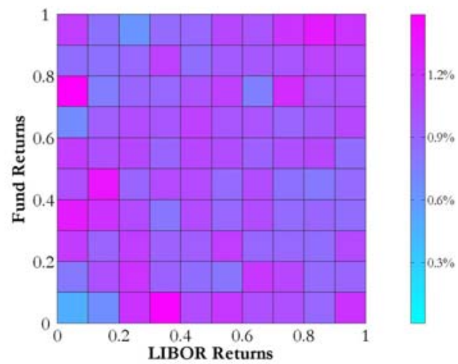


e) Emerging Markets (ρ = -0.17, β = 0.12)

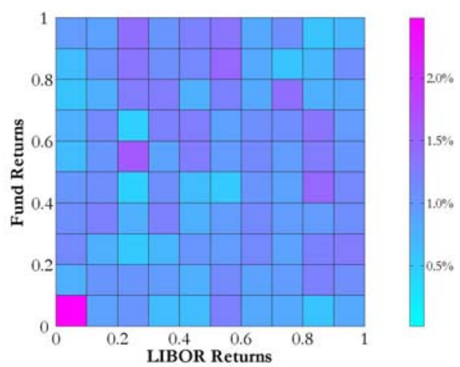
Figure 6. Cross-Sectional Rank-Rank Plots of Fund Returns and Three Month LIBOR Returns



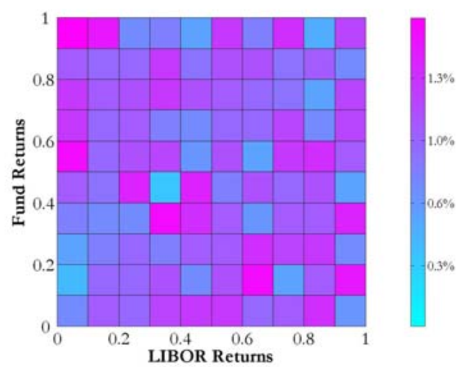
f) Equity Market Neutral (ρ = 0.07, β = 0.02)



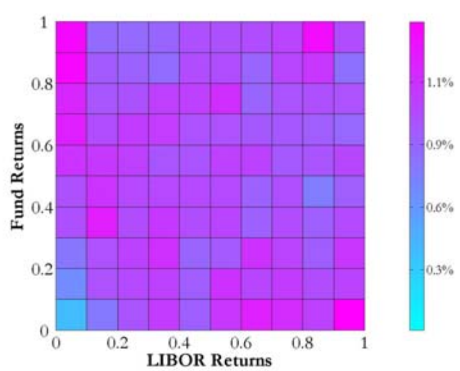
g) Event Driven (ρ = -0.04, β = -0.02)



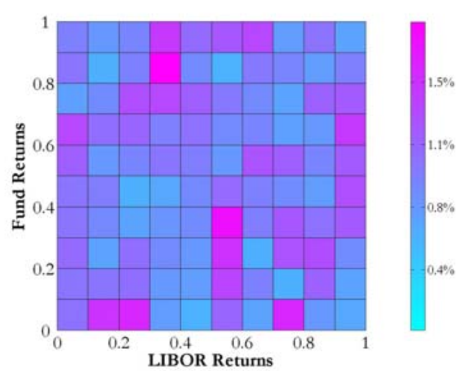
g) Fixed Income Arbitrage (ρ =-0.05, β = -0.02)



h) Global Macro (ρ = -0.03, β = -0.02)



h) Long Short Equity (ρ = 0.00, β = 0.00)



i) Managed Futures (ρ = -0.02, β = -0.01)

Figure 6. Cross-Sectional Rank-Rank Plots of Fund Returns and Three Month LIBOR Returns (continued)