Hedge Fund Tail Risk*

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Abstract

This paper uses quantile regressions to document the increase in hedge funds' Value-at-Risk (VaR) conditional on other styles being under distress and (predictable) spill-over effects to the banking sector. This increase of conditional VaR is due to an increase in bivariate dependencies in times of stress. We identify six common factors that explain the tail dependence across hedge fund styles. This set of risk factors also explains a large part of hedge funds' expected returns, which unlike the Value-at-Risk, affect flows into and out of hedge funds style.

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1 Introduction

Our financial architecture underwent a dramatic transformation in the last two decades with hedge funds taking on an ever increasing role. Hedge funds' assets under management – after adjusting for leverage – are now comparable to the total size of US investment banks' balance sheets and represent nearly 25% of GDP. The emergence of hedge funds as key financial intermediaries is intimately linked to this continuous process of financial innovation. In today's markets the risk of individual assets is repackaged and tranched into different components using derivatives. With this ever increasing tradability and securitization of financial assets such as loan portfolios, corporate debt, credit card payables, mortgages etc., hedge funds now take on risks that have traditionally been kept on banks' balance sheets.

The collapse of Long Term Capital Management (LTCM) in 1998 made clear that the failure of a hedge fund can threaten the stability of the financial system. The opaqueness of hedge funds' exposures and lack of regulatory oversight further raises the question whether hedge funds increase the likelihood of systemic crisis. In a liquidity spiral, initial losses in some asset class lead to higher margins, rapid asset sales, and reduction in mark-to-market wealth, which in turn leads to additional losses and potential spillovers into other asset classes (Brunnermeier and Pedersen (2007)).[1] Banks and particularly prime brokers, who have credit risk exposure to hedge funds, suffer potentially large losses if many hedge funds experience distress at the same time. Therefore from a financial stability point of view, it is important to understand which hedge fund styles tend to experience simultaneous large losses and to what extent the banking sector is shielded from hedge fund distress.

[1] The liquidity spiral of July/August 2007 that lead to a systematic unwinding of factor based portfolios among quant funds suggests a high comovement in quant fund returns in times of crisis. See Wall Street Journal August 24, 2007 "How the Quant Playbook Failed".

In this paper, we use quantile regression, which naturally yield our measure of tail risk – the Value-at-Risk (VaR) – to empirically study the interdependencies between different hedge fund styles at times of crisis, and analyze the spillover effects to the banking system. We present five main results: (i) our new tail risk dependence measure, $CoVaR$ – defined as hedge funds' VaR conditional on the fact that some other hedge fund style is in distress – is significantly higher than the (unconditional) VaR, (ii) "tail dependence" sensitivities are higher in times of distress, (iii) low returns of fixed income hedge funds predict a higher Value-at-Risk for investment banks in the subsequent months. To document this (delayed) spill-over effect to the banking sector, we introduce a "Granger-tail causality test". Furthermore, (iv) we identify six risk factors that explain the tail dependence across hedge fund styles and the banking sector and argue that (v) these risk factors also explain a large part of hedge funds' expected returns. We also find – consistent with existing literature – that past returns affect capital flows across strategies and over time, but – surprisingly – the Value-at-Risk does not affect capital flows. Hedge fund managers thus have incentives to load on tail risk for two reasons: it increases both the managers' incentive fee (percentage of the fund's profit) and the management fee (percentage of assets under management).

Our paper contributes to the growing literature that sheds light on the link between hedge funds and the risk of a systemic crisis. Boyson, Stahel, and Stulz (2006) also document contagion across hedge fund styles using logit regressions on daily and monthly returns. However, they do not find evidence of contagion between hedge fund returns and equity, fixed income and foreign exchange returns. In contrast, we show that our pricing factors explain the increase in comovement among hedge fund styles in times of stress. Chan, Getmansky, Haas, and Lo (2006) document an increase in correlation across hedge funds, especially prior to the LTCM crisis and after 2003. Adrian (2007) points out that the increase in correlation since 2003 is due to a reduction in volatility – a phenomenon that occurred across many financial assets – rather than an increase in covariance.

Asness, Krail, and Liew (2001) and Agarwal and Naik (2004) document that hedge funds load on tail risk in order to boost their CAPM-α. Agarwal and Naik (2004) capture the tail exposure of equity hedge funds with non-linear market factors that take the shape of out-of-the-money put options. Patton (2007) develops several "neutrality tests" including a test for tail and VaR neutrality and finds that many so-called market neutral funds are in fact not market neutral. Bali, Gokcan, and Liang (2007) and Liang and Park (2007) find that hedge funds that take on high left-tail risk outperform funds with less risk exposure. In addition, there is a large and growing number of papers that explain average returns of hedge funds using asset pricing factors (see e.g. Fung and Hsieh (2001, 2002, 2003), Hasanhodzic and Lo (2007)). Our approach is different in the sense that we study factors that explain the co-dependence across the tails of different hedge fund styles.

The paper is organized in five sections. In Section 2, we study the pairwise relationships between the returns to different hedge fund styles, and the relationships between hedge fund styles and other financial intermediaries. In Section 3, we estimate a risk factor model for the hedge fund returns. We document that six commonly traded risk factors explain hedge fund returns well, and that they particularly explain the increase of $CoVaR$ relative to unconditional VaR. In Section 4, we study the incentives of hedge funds to take on tail risk. Finally, Section 6 concludes.

2 q-Sensitivities and CoVaR

In this section, we document that pairwise dependence of the returns to hedge fund styles is significantly higher in times of stress. As a result, the Values-at-Risk of fund styles conditional on other funds is higher in times of stress than in normal times. We also study the relation between hedge fund returns and the returns to other financial institutions in times of stress, both contemporaneously and in a predictive sense.

2.1 Hedge Fund Return Data

Hedge funds are private investment partnerships that are largely unregulated. Studying hedge funds is more challenging than the analysis of regulated financial institutions such as mutual funds, banks, or insurance companies, as only very limited data on hedge funds is made available through regulatory filings. Consequently, most studies of hedge funds thus rely on self-reported return data.[2] We follow this approach and use the hedge fund style indices by Credit Suisse/Tremont.

There are several papers that compare the self-reported returns of different vendors (see e.g. Agarwal and Naik (2005)), and some research compares the return characteristics of hedge fund indices with the returns of individual funds (Malkiel and Saha (2005)). The literature also investigates biases such as survivorship bias (Brown, Goetzmann, and Ibbotson (1999) and Liang (2000)), termination and self-selection bias (Ackermann, McEnally, and Ravenscraft (1999)), backfilling bias, and illiquidity bias (Asness, Krail, and Liew (2001) and Getmansky, Lo, and Makarov (2004)). We take from this literature that hedge fund return indices do not constitute ideal sources of

[2]A notable exception is a study by Brunnermeier and Nagel (2004) who use quarterly 13F filings to the SEC and show that hedge funds were riding the tech-bubble rather than acting as price-correcting force.

data, but that their study is useful, and the best that is available. In addition, there is some evidence that the Credit Suisse/Tremont indices appear to be the least affected by various biases (Malkiel and Saha (2005)).

[Table 1]

Summary statistics for January 1994 - June 2006 of the monthly excess returns of the overall hedge fund index and the ten style indices are given in Table 1 (Panel A). These styles have been extensively described in the literature (see Agarwal and Naik (2005) for a survey), and characterizations can also be found on the Credit Suisse/Tremont website (www.hedgeindex.com). We report the hedge fund returns in the order of their weights in the overall index as of December 2006. These weights are also reported in the third to last column of Panel A in Table 1. We also report the returns of three additional financial institutions in Panel B: commercial banks, investment banks, insurance companies. In addition, we report the summary statistics of the return CRSP market excess return, which we sometimes interpret as a proxy to a well diversified mutual fund. The commercial bank and insurance company returns are from the 49 industry portfolios of Ken French's website (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html). The investment bank returns are the value weighted returns of Morgan Stanley, Merrill Lynch, Goldman Sachs, Bear Sterns, and Lehman Brothers from CRSP. Note that traditional financial intermediaries are traded and hence their returns – unlike the accounting returns used in hedge fund indices – also reflect expected changes in goodwill and reputation.

The Sharpe ratio of the hedge fund index (0.27 monthly) is nearly twice as high as the Sharpe ratio of the market index (0.15 monthly). It is also higher than the Sharpe ratio of the other financial institutions (0.20 for investment banks, 0.21 for commercial banks, and 0.18 for insurance companies). There is a wide disparity of Sharpe ratios across styles: equity market neutral achieves the highest Sharpe ratio (0.60), while dedicated short has a negative Sharpe ratio (-0.09). Sharpe ratios and the December 2006 sectoral weights do not appear to be highly correlated (the correlation is in fact 15% and statistically insignificant), but average returns over the 1994-2006 period are highly and significantly correlated with the December 2006 weights (the correlation is 56%). Since hedge funds invest part of their wealth in highly illiquid instruments with stale or "managed" prices, they can smooth their returns and manipulate Sharpe ratios (see e.g. Asness, Krail, and Liew (2001) and Getmansky, Lo, and Makarov (2004)).

The hedge fund index has less negative skewness than the market return (-0.03 versus -0.79), but higher kurtosis (5.55 versus 4.93). There is also large variation of skewness and kurtosis across styles. Styles with higher leverage generally appear to have more negative skewness. Normality is rejected on the basis of either skewness or kurtosis for all styles, as well as the other financial institutions and the market return. Thus, consistent with previous findings, the returns to hedge funds have both skewed and fat tailed returns relative to normality.

The most negative monthly returns are lower for the overall hedge fund index than for the market or other financial institutions. This finding is also confirmed by looking at the 5% percentile: it is -2.58% monthly for the hedge fund index, versus -6.41% for the market. The finding that the left tail of hedge fund returns has excess skewness and kurtosis relative to a normal distribution, but lower skewness and kurtosis than the market is consistent with Brunnermeier and Nagel's (2004) finding that hedge funds are good market timers.

2.2 Quantile Regressions

We make use of quantile regressions to study the dependence of hedge fund returns in times of crisis. Quantile regressions were developed by Koenker and Bassett (1978) and Bassett and Koenker (1978). A literature review can be found in Koenker (2005).

We provide a short overview of quantile regressions in the context of linear factor models in the Appendix. In this section, we use quantile regressions to analyze bivariate relationships between styles. Consider the prediction of quantile regression of style i on style j:

$$\hat{R}_q^i = \hat{\alpha}_q^{ij} + \hat{\beta}_q^{ij} R^j \tag{1}$$

where $\hat{R}_q^i$ denotes the predicted value of excess return i for quantile q and R^j denotes the excess return of style j. Note that a median regression is the special case of a quantile regression where $q = 50\%$. From the definition of Value-at-risk, it follows directly that:

$$VaR_q^i | R^j = \hat{R}_q^i \tag{2}$$

Note that the usual definition of *VaR* is the negative of our definition. Thus the predicted value from the quantile regression of returns of style i on style j gives the Value-at-Risk conditional on R^j. In principle, this regression could be extended to allow for non-linearities by introducing higher order dependence of returns to style i as a function of returns to style j.

Definition 1 *We denote the* CoVaR^{ij}, *the* VaR *of style i conditional on the (unconditional) VaR of style j by:*

$$\text{CoVaR}_q^{ij} := VaR_q^i | VaR_q^j = \hat{\alpha}_q^{ij} + \hat{\beta}_q^{ij} VaR_q^j. \tag{3}$$

Thus CoVaR_q^{ij} *gives the* VaR_q *of strategy* i *conditional on the unconditional* VaR_q *of strategy* j.

We sometimes say that $CoVaR^{ij}$ is the VaR of style i conditional on style j being in distress. Our definition of $CoVaR$ is a measure of contagion and reflects the co-movements of the VaRs across two different hedge fund styles. It differs from the often used conditional VaR (CVaR), mean excess loss, expected/mean shortfall, or tail VaR, which are all defined for a single strategy as $E\left[R^i|R^i \leq VaR^i\right]$.

While quantile regressions are regularly used in many applied fields of economics, its application to finance has up to now been rather limited. Notable exceptions are econometric papers like Bassett and Chen (2001) and Chernozhukov and Umantsev (2001) as well as the working papers by Barnes and Hughes (2002) and Ma and Pohlman (2005). This is surprising to us, since the 5% quantile of the return directly provides an estimate of the (negative of) Value-at-Risk, a widely used risk-measure.

2.3 q-Sensitivities

Average hedge fund sensitivities increase in times of stress. This can be seen from Table 2, where we report the q-sensitivities across the hedge funds styles (as well as the q-sensitivities with other financial intermediaries) for the $q = 50\%$ quantile and the $q = 5\%$ quantile (Panels A and B, respectively). These q-sensitivities are the coefficients β_q^{ij} of Equation (1). The average sensitivity for the bivariate median regressions (Equation (1) with $q = 50\%$) across all possible combinations of the ten hedge fund styles is 32%, while it is 53% for the sensitivities in the 5% quantile regressions. Instead of assigning the same weight to each style, we also report the average sensitivities weighted by the December 2006 value times leverage, and find averages of 33% for the

50% sensitivities (median regressions), versus 56% for the 5% sensitivities. Average sensitivities are thus more than two thirds higher in times of stress (as proxied by the 5% sensitivities) compared to normal times (as proxied by the 50% sensitivities).

[Table 2]

We can also see that the q-sensitivities between the hedge fund styles and other financial intermediaries increases in the left tails of the return distributions. In particular, the average exposures between the ten hedge fund styles, and the other financial intermediaries is 42% for the median regression, and 70% for the 5% quantile regressions.

Table 2 also reveals interesting patterns across individual styles. Each column of the table gives a particular right hand side variable of the quantile regressions, while the styles in the first column of the table correspond to the left hand side returns. For example, the sensitivity of global macro returns with respect to fixed income arbitrage is 7% in the median regression, but increases to 26% in the 5% regression. Conversely, the sensitivity of fixed income arbitrage with respect to global macro is 105% in normal times, but increases to 114% in times of stress.

The increase in sensitivities among hedge fund styles in times of stress has previously been noted by Boyson, Stahel, and Stulz (2006). Boyson, Stahel, and Stulz (2006) do not use quantile regressions, but produce dummies for the worst 5% of returns of the left hand side return in an OLS regression, and refer to this increase in dependencies as “contagion”.

2.4 Increases in *CoVaRs*

As a consequence of the increase in average sensitivities among hedge fund styles, the *CoVaRs* increase. This can be seen in Table 3, where we report the matrix of percentage increases in *CoVaRs*, relative to their unconditional values:

$$\frac{CoVaR^{ij} - VaR^{i}}{VaR^{i}}$$

Reporting the percentage increase relative to the unconditional VaRs instead of the CoVaR itself has the advantage that it normalizes data across strategies with different unconditional VaRs. The unconditional VaRs are reported in the first column of the table and corresponds to the 5th percentile of the return distribution, also reported in Table 1. The average unconditional VaR of the different hedge fund styles is -3.35% (it is -2.77% for the value weighted average), and -6.72% for the other financial intermediaries. The average percentage increase of the *CoVaRs* is 30.57, thus the average *CoVaR* is $-3.35\% * (1 + 30.57\%) = -4.38\%$.

[Table 3]

As one would expect, these effects are not totally symmetric. For example, fixed income funds and multi-strategy funds have roughly the same (unconditional) *VaR* of -1.51, -1.33 respectively. However, when multi-strategy funds are in distress, the *VaR* of fixed income funds is 52% higher, while in periods of distress for fixed-income funds, the *VaR* of multi-strategy is increased by roughly 77%.

2.5 Forecasting Distress - Tail Granger Causality Test

So far we focused on contemporaneous relationship between returns. Next, we incorporate quantile regressions into a Granger causality test to determine whether hedge fund returns predict distress in other financial intermediaries (in the sense of an increased Value-at-Risk), and vice versa. More specifically, we "quantile regress"

$$R_q^i = \alpha_q^{ij} + \beta_q^{ij} R_{t-1}^j + \gamma_q R_{t-1}^i + u_t^{ij}$$

and test whether β_q^{ij} for $q = 5\%$ are significantly different from zero.

[Table 4]

Our findings, presented in Table 4, show that multi-strategy, fixed-income, convertible arbitrage and dedicated short funds predict a statistically significantly higher Value-at-Risk in the investment banking sector. The converse and a link to the commercial banking sector is not statistically significant, which is most likely due the fact that at the beginning of our data sample 1994, the interdependence between hedge funds and commercial banks was weaker than it is today. As commercial banks are entering more and more into the investment banking business (whose trading resembles to a large extent that of hedge funds), we would expect that the "tail Granger causality" that we document for investment banks might also show up for commercial banks.

3 Identifying Tail Factors

Having established that Value-at-Risk of hedge fund style i or of banks increases when the return of style j is in distress, in this section we identify factors that explain this "tail dependence". We argue that a factor structure explains this tail dependence, if the CoVaR after offloading the risk associated with these factors roughly coincides with the unconditional offloaded VaR, that is, if the excess tail dependence for residuals is much lower compared to the dependence of the raw returns. We first outline our six factors, before creating offloaded returns. We distinguish between two offloaded returns: (i) the residuals of an OLS regression whose conditional expectation is independent of the realization of the factor returns and (ii) the residuals of a 5% quantile regression, whose 5% VaR does not depend on the factor returns.

3.1 Tail Factors - Description and Data

We select six factors that capture the increase in co-movement across hedge fund styles' VaRs. All of them have solid theoretical foundations, capturing certain aspects of risks and hence, are not simply due to data mining. They are also liquid and easily tradable. We restrict ourselves to a small set of six risk factors to avoid overfitting the data. Our factors are:

(i) CRSP *market return* in excess to the 3-month bill rate reflecting the equity market risk. The Center for Research in Security Prices (CRSP) market index is a broad benchmark reflecting the value weighted of all publicly traded securities;

(ii) *VIX* straddle excess return to capture the implied future volatility in the stock market. This implied volatility index is available on Chicago Board Options Exchange's website. To get a tradable excess return series we calculate the straddle return of a hypothetical at-the-money straddle position that is based on the VIX implied volatility and substract the 3-month bill rate.

(iii) the *variance swap return* to capture the associated risk premium for risky shifts in volatility. The variance swap contract pays off the difference between the realized variance over the coming months and its delivery price at the beginning of the month. Since the delivery price is not commonly observable over our whole sample period, we use – as is common practice – the VIX squared normalized to 21 trading days, i.e. $(\text{VIX*}21/360)^2$. The realization of the index variance is computed from daily S&P 500 index data for each month. Note also since the initial price of the swap contract is zero, returns are automatically excess returns.

(iv) a short term *"liquidity spread"*, defined as the difference between the 1-month repo rate and the 1-month bill rate measures the short-term counterparty liquidity risk. We use the 1-month general collateral repo rate that is available on Bloomberg, and obtain the 1-month Treasury rate from the Federal Reserve Bank of New York.

In addition we consider the following two fixed-income factors that are known to be indicators in forecasting the business cycle and also predict excess stock returns (Estrella and Hardouvelis (1991), Campbell (1987), and Fama and French (1989)).

(v) the *slope of the yield curve*, measured by the yield-spread between the 10-year Treasury rate and the 3-months bill rate.

(vi) the *credit spread* between BAA rated bonds and the Treasury rate (with same maturity of 10 years).

The last three factors are from the Federal Reserve Board's H.15 release. All data are monthly from 01:1994 to 07:2007.

The literature has studied related factors. Boyson, Stahel, and Stulz (2006) use the S&P500, Russell 3000, change in VIX, FRB dollar index, Lehman US bond index and the 3-Month Bill return as factors, but – unlike our study – they do not find a link between these factors and contagion. Agarwal and Naik (2004) also focus on tail risk. In addition to out of the money put and call market factors they use the Russell 3000, MSCI excluding US (bonds), MSCI emerging markets, HML, SMB, MOM, Salomon

Government and corporate bonds, Salomon world government bonds, Lehman high yield, Federal Reserve trade weighted dollar index, GS commodity index and change in default spread. Factors used in Fung and Hsieh (1997, 2001, 2002, 2003) differ depending on the hedge fund style they analyze. An innovative feature of their factor structure is to incorporate lookback options factors that are intended to capture momentum effects. We opted not to include this factor since restricted ourselves only to highly liquid factors. Fung, Hsieh, Naik, and Ramadorai (2008) try to understand performance of fund of fund managers. They employ the S&P 500 index as factor; a small minus big factor; the excess returns on portfolios of lookback straddle options on currencies, commodities and bonds; the yield spread – our factor (v) – and the credit spread – our factor (vi). Finally, Chan, Getmansky, Haas, and Lo (2006) use the S&P 500 total return, bank equity return index, the first difference in the 6-months LIBOR, the return on the U.S. Dollar spot rate, the return to a gold spot price index, the Dow Jones / Lehman Brothers bond index, Dow-Jones large cap - small cap index, Dow Jones value minus growth index, the KDP high yield minus U.S. 1-year Treasury yield, the 10-year Swap / 6-month Libor spread, and the change in CBOE's VIX implied volatility index. Bondarenko (2004) introduced the Variance swap contract as a new factor.

In our robustness section we show whether our results change for these alternative factor specifications .

3.2 Off-loaded Returns

After having specified our factors, we study next how offloading the tail risk that is associated with these affects the returns. We consider two different ways to construct offloaded returns. As an intermediate step we first look at "OLS offloaded returns" which are the residual of the OLS regression of raw returns on our six factors. Then, we look at the "quantile offloaded returns" we are primarily interested in, the residuals of the 5%-quantile regression of raw returns on our six factors. Note that VaR of the quantile offloaded returns is independent of the realization of the factors.

Panel A of Table 6 repeats the raw returns listed in Table 1 to facilitate the comparison with the quantile offloaded returns reported in Panel B.

[Table 6]

The following differences between Panel A and B stand out: First, offloading the risk associated with our factors significantly reduces the average mean return and Sharpe ratio if one weights each strategy by its size. The reduction is small if fund style are equally weighted. However, this is primarily driven by the overrepresentation of dedicated short-specialists – a hedge fund style that comprises only 1 percent of the fund size universe – since their quantile offloading returns is relatively high. Looking at individual styles, one notes that some off-leaded mean returns and Sharpe ratio even enter negative territory. Our model's αs are not very large – and they are by definition the same for the raw returns and offloaded returns. The CAPM-α, using CRSP excess market returns, also drops notably after offloading the risk associated with our factors. The average CAPM declines from .35 to .11. Note that we take the simple average of αs instead of the average of the absolute amounts of αs, since it is not easy to short a hedge fund style. Finally, note that hedge fund and bank returns are not normally distributed. Most styles and the index exhibit negative skewness and positive excess kurtosis. The Royston's (1991) tests for normality confirms this. It give the p-values whether skewness is zero and kurtosis is three – the values for the normal distribution. The kernel densities of Figure 1 reveal that offloading reduces the fat left tail, while it doesn't affect the right tail much.

[Figure 1]

3.3 q-Sensitivities of Off-loaded Returns

As we did for the raw returns in Section 2, we replicate the bivariate 5%-quantile regressions for the offloaded returns. In other words, we quantile regress the offloaded returns of style i on the offloaded returns of style j. Table 8 reports quantile regression coefficients, our sensitivity measures for the offloaded returns for $q = 5\%$. Off-loaded returns are residuals of the OLS factor regression in Panel A and the residual of the quantile factor regression constructed in Panel B.

[Table 7]

Ultimately, we are interested in whether our six factors capture the tail dependence among hedge funds' raw returns. They do so, if the bivariate-sensitivities of the offloaded returns in Table 8 are significantly lower than the ones for the raw returns reported in Table 2, Panel B in Section 2. The average bivariate 5%-sensitivity decreases from 53% to 34% for the OLS offloaded returns and to 20% for the quantile offloaded returns. The decline is even more pronounced for the banking and insurance sector. The average cosensitivity drops from 70% to 25%, 14% respectively.

Another striking feature of Table 7 is that there are many negative entries in the Commercial bank row. That is, the offloaded VaR of commercial banks seems to improve as returns of various, especially the large, hedge fund styles worsen. This finding is surprising at first sight but is consistent with "reintermediation phenomenon" caused by flight to quality. As investors shed risky assets in times of crisis, cash pours into commercial banks and hence, banks' funding liquidity improves. Hence, they are natural liquidity providers at these times (Gatev and Strahan (2006)), which seems to boost their offloaded returns. However, their overall returns still suffer since they are also adversely affected by our risk factors. The coefficients for insurance companies point in a similar direction, but they differ in magnitude.

3.4 *CoVaRs* of Off-loaded Returns

q-Sensitivities give a good sense about the directional impact of conditioning, but they do not allow a good comparison across more and less volatile hedge fund styles. The percentage increase in CoVaR over the unconditional VaR provides the right normalization and hence more information on the extent to which our factors reduce the tail dependence. Table 8 reports percentage increases in CoVaR over the unconditional VaR. In Panel A offloaded returns are the residual of the OLS regression of returns on our six factors. In Panel B we use the residual of the 5% quantile regression as the offloaded returns. After offloading risks associated with these factors, the Value-at-Risk of the residual monthly returns is in fact only -3.02% (Panel A) and -3.04% (Panel B).

[Table 8]

Our factors capture the co-dependence among hedge fund styles and other financial intermediaries if the percentage increase in CoVaRs for the offloaded returns is markedly smaller than the one reported for raw returns in Table 3. Indeed, the average percentage increase due to conditioning on other fund styles being in trouble is only 19.59% of the -3.02% (Panel A), 9.02% of -3.04% (Panel B). Recall without offloading the tail dependence is much higher – conditioning on some other fund style being in distress on average increased the Value-at-Risk on average by 38.15% (Table 3). Taking the weighted average instead of the simple average, the drop is from 30.57% for raw returns (Table 3) to 15.53% for OLS offloaded returns (Panel A) or 6.32% quantile offloaded returns (Panel B). The drop is more dramatic for the banking and insurance sector.

Also note that the hedge fund strategy Equity Market Neutral (EMN) has the lowest unconditional VaR, which explains why the percentage increase in CoVaR is high after conditioning on certain hedge fund styles.

4 Incentives to Load on Tail Risk

Section 2 documents that tail risk of hedge funds and other financial institutions increases during times of distress. Section 3 identifies tradable factors that explain a large part of this increase in tail risk. We next ask whether hedge funds have an incentive to offload this tail risk.

4.1 Cost of offloading factor risks

Hedge fund managers, investors, banks, or fund of fund managers can offload the risk associated with these factors without incurring large trading costs since our factors tradable and highly liquid. Consequently offloading is α-neutral within our model. However, the comparison of Panels A and B of Table 6 show that offloading significantly reduces the weighted average monthly return from .26 to 0.08. Stated differently, a large extent of hedge funds' outperformance relative to the market index is a direct result of their loading on these "tail" factors, especially the variance swap factor. In short, there appears to be a risk-return trade-off between returns and conditional Value-at-Risk in hedge fund returns.

4.2 Flow analysis

If reducing sensitivity to these "tail risk factors" substantially lowers hedge funds' expected return, the question arises whether hedge fund managers have an incentive to do so. A typical hedge fund manager receives a performance fee of 20% of the realized profits plus 2% of the value of assets under management. Hence, limiting his risk-sensitivity to these (high-return) factors lowers his expected compensation except if it leads to significant inflows into his fund. We study these flows and find that flows are sensitive to past monthly and annual returns or past (annual rolling) Sharpe ratios, but not to the hedge funds' VaR or the standard deviation of its returns. The standard deviation is calculated with an annual rolling window, while the VaR is computed as the predicted value from a 5% quantile regression on the six pricing factors with a minimum of 24 months of data.

[Table 9]

The lack of sensitivity of fund flow with respect to two risk measures – standard deviation and VaR – gives the fund manager no incentive to offload the risks associated with our factors. This suggests that investors either expect hedge fund managers to take on this risk or investors are naive and hedge fund managers take advantage of this fact.

5 Robustness

5.1 Alternative measures of dependency

The comparison of q-sensitivities from the 5%- and 50%-quantile regressions of Table 2 can be interpreted as a comparison of sensitivities across states of the world. Table

2 shows that average sensitivities are higher in bad times (the average 5% quantile sensitivity is 52%) than in normal times (the average 50%-quantile sensitivity is 32%). In Figure 2, we plot the average sensitivities across the hedge fund styles for all quantiles between 5% and 95% for total returns, OLS offloaded returns, and 5% offloaded returns. The plot shows that the sensitivities across quantiles is relatively flat for the 5%-offloaded returns. In contrast, average sensitivities are sharply decreasing along the quantiles for the total returns, and are also decreasing for the OLS offloaded returns.

[Figure 2]

Instead of looking at sensitivities across states of the world, we can also investigate the evolution of sensitivities over time. To do so, we estimate a multivariate BEKK-ARCH(12) model, and extract the evolution of covariances across the strategies over time. We plot the average of the covariances across the ten strategies in Figure 3.

[Figure 3]

The covariances for the 5%-offloaded returns are clearly less volatile than for the total returns. In particular, estimated average covariances spiked during the LTCM crisis in the third quarter of 1998, and in January 2000. In contrast, the average covariances of 5%-offloaded returns increased much less during those volatile times.

5.2 Alternative measures of tail risk

Value-at-Risk – our main measure of tail risk – is only one possible characterization of tail risk. Many alternative measures have been proposed. First of all, Value-at-Risk at lower quantiles can be used. Second, other measures of tail risk can be used. A particularly appealing measure of tail risk that has been proposed in the literature

Artzner, Delbaen, Eber, and Heath (1999) is the expected shortfall. It is defined as the average loss below the VaR. In order to make sure that our results are robust to this measure, we computed the expected shortfall of returns as the average CoVaR for 1%, 2%, 3%, 4%, and 5%, and report the results in Table 10.

[Table 10]

By comparing the two panels, we see that the unconditional expected shortfall is -3.99% for total returns of hedge funds, and -3.51% for the 5% offloaded returns. The increase of expected shortfall conditional on the other strategies is 28% higher for total returns, and only 5.94% higher for the offloaded returns.

5.3 Alternative hedge fund data

There are several providers of hedge fund indices that use different hedge funds and different methodologies to compute style indices. Two alternative data providers are Hedge Fund Research (HFR, at www.hedgefundresearch.com), and Morningstar/Altvest (at www.altvest.com). Tables 11 and 12 report the CoVaRs for these two alternative databases.

[Table 11] [Table 12]

Our main result that the increase of CoVaRs conditional on distress of the other strategies or institutions is higher than the unconditional VaRs holds for these alternative datasets. We can also see that offloaded returns have a markedly lower increase in CoVaRs. A striking feature of the alternative datasets is that they have generally lower unconditional VaRs, but more pronounced increases in the CoVaR relative to the unconditional VaR in comparison to the Credit Suisse / Tremont indices.

5.4 Alternative factors

– To be written –

6 Conclusion

– To be written –

A Appendix

This appendix is a short introduction to quantile regressions in the context of a linear factor model. Suppose that excess returns R_t have the following (linear) factor structure:

$$R_t = \gamma_0 + X_t\gamma_1 + (\gamma_2 + X_t\gamma_3)\,\varepsilon_t \tag{4}$$

where X_t is a vector of risk factors. Factors are assumed to be excess returns. The error term ε_t is assumed to be i.i.d. with zero mean and unit variance and is independent of X_t so that $E[\varepsilon_t|X_t] = 0$. Our returns are generated by a process of the "location-scale" family, so that both the conditional expected return $E[R_t|X_t] = \gamma_0 + X_t\gamma_1$ and the conditional volatility $Vol_{t-1}[R_t|X_t] = (\gamma_2 + X_t\gamma_3)$ depend on a set of factors. The coefficients γ_0 and γ_1 can be estimated consistently via OLS:[3]

$$\hat{\gamma}_0 = \alpha_{OLS} \tag{5}$$

$$\hat{\gamma}_1 = \beta_{OLS} \tag{6}$$

We denote the cumulative distribution function (cdf) of ε by $F_\varepsilon(\varepsilon)$, and the inverse cdf by $F_\varepsilon^{-1}(q)$ for percentile q. It follows immediately that the inverse cdf of R_t is:

$$\begin{aligned} F_{R_t}^{-1}(q|X_t) &= \gamma_0 + X_t\gamma_1 + (\gamma_2 + X_t\gamma_3)\,F_\varepsilon^{-1}(q) \\ &= \alpha(q) + X_t\beta(q) \end{aligned} \tag{7}$$

[3]The volatility coeffients γ_2 and γ_3 can be estimated using a stochastic volatility or GARCH model if distributional assumptions about ε are made, or via GMM. Below, we will describe how to estimate γ_2 and γ_3 using quantile regessions, which do not rely on a specific distribution function of ε.

where

$$\alpha(q) = \gamma_0 + \gamma_2 F_{\varepsilon}^{-1}(q) \tag{8}$$

$$\beta(q) = \gamma_1 + \gamma_3 F_{\varepsilon}^{-1}(q) \tag{9}$$

with quantiles $q \in (0,1)$. We also call $F_{R_t}^{-1}(q|X_t)$ the conditional quantile function and denote it by $Q_{R_t}(q|X_t)$. From the definition of VaR:

$$VaR_q|X_t = \inf_{VaR_q} \{\Pr(R_t \leq VaR_q|X_t) \geq q\} \tag{10}$$

follows directly that

$$VaR_q|X_t = Q_{R_t}(q|X_t) \tag{11}$$

the q-VaR in returns conditional on X_t coincides with conditional quantile function $Q_{R_t}(q|X_t)$. Typically, we are interested in values of q close to 0, or particularly $q = 1\%$. Note that by multiplying the (absolute value of the) VaR in return space the by hedge fund capitalization gives the VaR in terms of dollars.

We can estimate the quantile function via quantile regressions:

$$\left[\alpha_q, \beta_q\right] = \arg\min_{\alpha_q, \beta_q} \sum_t \theta_q\left(R_t - \alpha_q - X_t\beta_q\right) \text{ with } \theta_q(u) = (q - I_{u \leq 0})\, u \tag{12}$$

See Koenker and Bassett (1978). Review Koenker and Bassett (1978) and Chernozhukov and Umantsev (2001).

Remark 1 *Note that:*

$$\begin{aligned}\int_0^1 Q_{R_t}(q|X_t)\,dq &= \int_0^1 \left(\alpha^q + X_t\beta(q)\right)dq \\ &= \gamma_0 + X_t\gamma_1 + (\gamma_2 + X_t\gamma_3)\int_0^1 F_\varepsilon^{-1}(q)\,dq \\ &= \gamma_0 + X_t\gamma_1 = E\left[R_t|X_t\right]\end{aligned}$$

as $\int_0^1 F_\varepsilon^{-1}(q)\,dq = \int \varepsilon dF(\varepsilon) = 0$. *So the OLS regression coefficients* $[\gamma_0, \gamma_1]$ *can be recovered from the quantile function by integrating over the quantiles.*

The difference between the quantile coefficients and the OLS coefficients is:

$$\begin{aligned}\alpha^q - \alpha^{OLS} &= \gamma_2 F_\varepsilon^{-1}(q) \\ \beta^q - \beta^{OLS} &= \gamma_3 F_\varepsilon^{-1}(q)\end{aligned} \tag{13}$$

So estimation of any two quantiles q and q' allows identification of γ_2 and γ_3.

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Figure 1: Kernel Densities of Total and 5%-Offloaded Returns

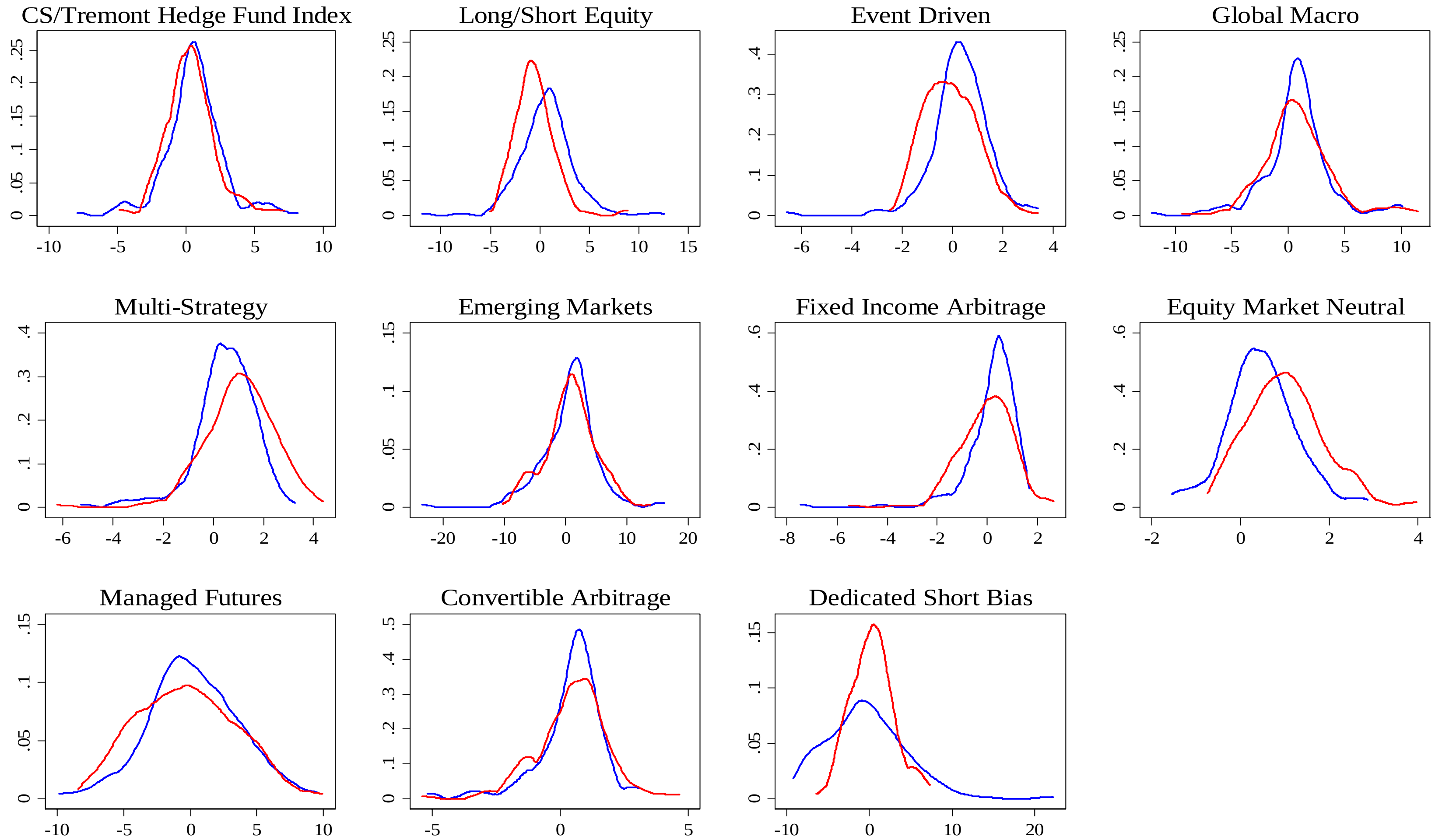

Figure 2: Average Sensitivities by Quantiles

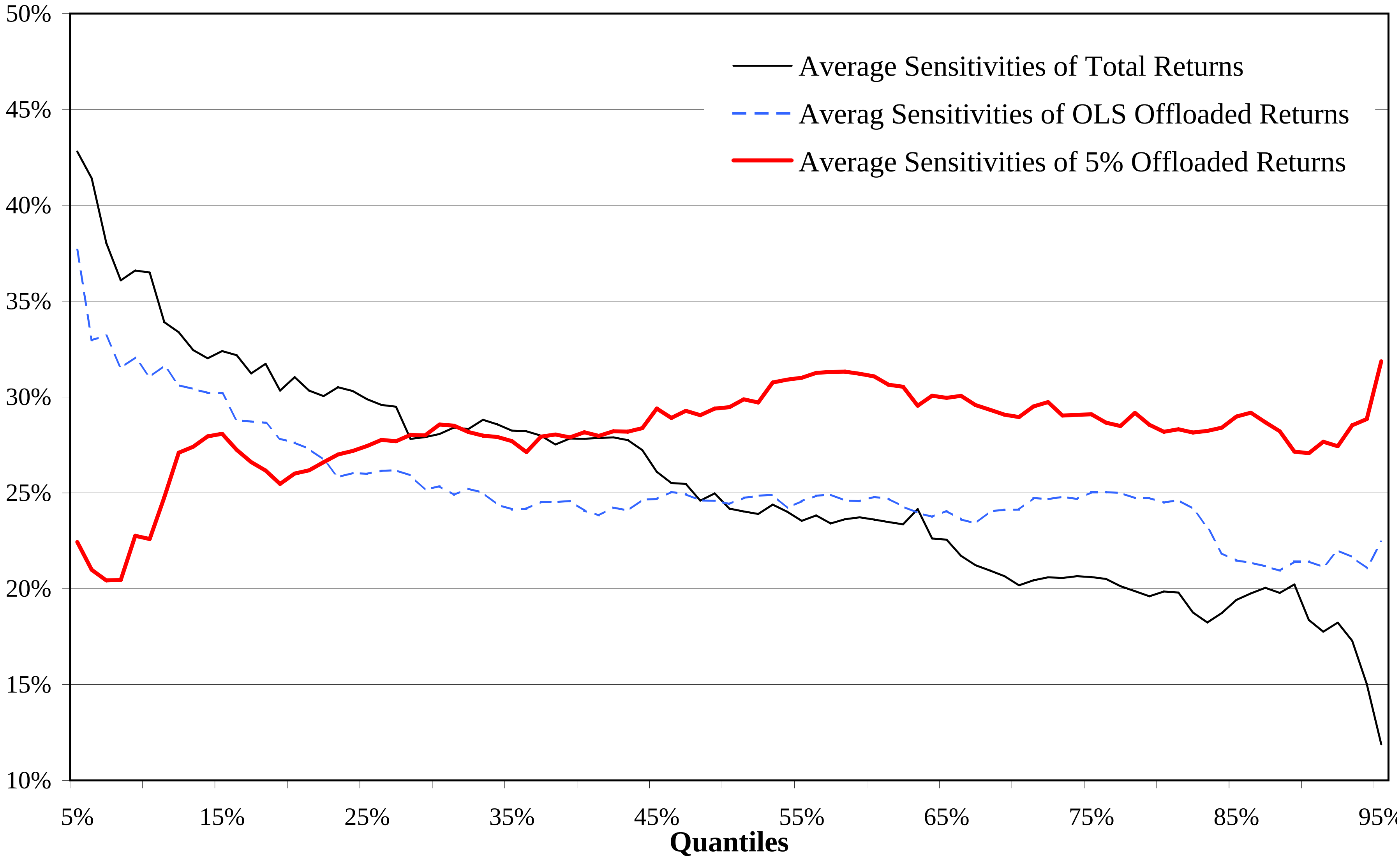

Figure 3: Average GARCH Covariances over Time

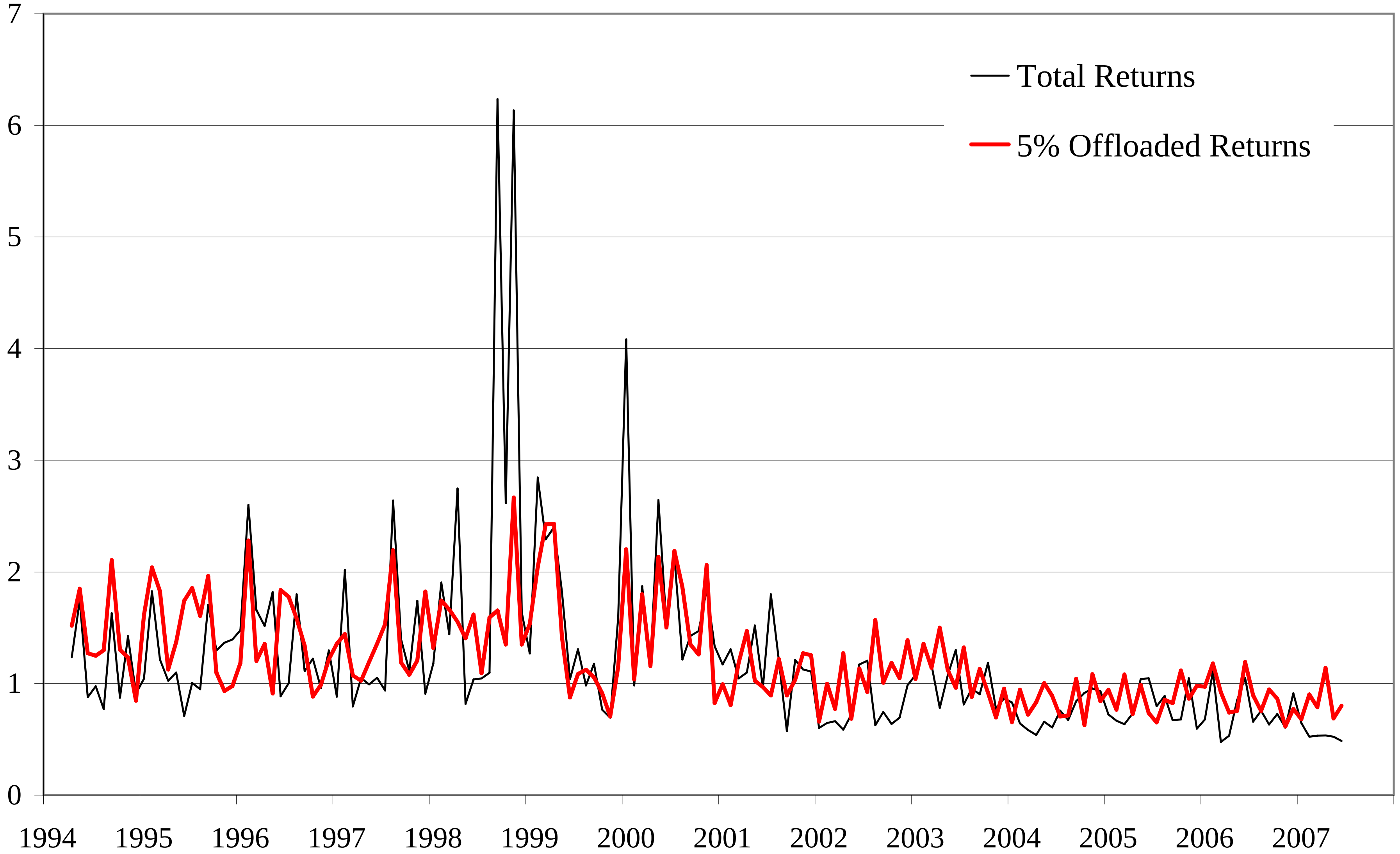

Table 1: Summary Statistics of Monthly Excess Returns by Strategies

Panel A reports summary statistics for the Credit Suisse / Tremont hedge fund index, and the ten Credit Suisse / Tremont hedge fund style returns. All returns are in excess of the three month Treasury bill rate. The Sharpe ratio is the ratio of mean excess returns to the standard deviation of excess returns. The tests for normality give the p-values of Royston's (1991) test that skewness / kurtosis are normal. The weights for each style are the weights that aggregate the ten styles to the overall Credit Suisse / Tremont index for December 2006. Leverage is computed from reported average leverage of individual funds in the TASS database for December 2006, and averaged by style. Panel B reports the value weighted equity returns (in excess of the three month Treasury bill rate) of five investment banks (Bear Stearns, Goldman Sachs, Merrill Lynch, Morgan Stanley, and Lehman Brothers) using data from CRSP. The commercial bank and insurance company returns are from Kenneth French's industry portfolios. The market return is the cum dividend value weighted CRSP return.

Panel A: Hedge Funds

							5th		Tests for Normality		Weight	Leverage	Weight*
	Sharpe	Mean	Std Dev	Skew	Kurt	Min	Percenti	Obs	Pr(Skew)	Pr(Kurt)	Dec-06	Dec-06	Leverage
Hedge Fund Index	0.27	0.58	2.17	-0.03	5.55	-7.98	-2.58	162	1%	0%	100%	183%	100%
Long/Short Equity	0.24	0.69	2.84	0.12	7.13	-11.86	-3.22	162	2%	0%	29%	118%	19%
Event Driven	0.26	0.31	1.16	-1.31	10.30	-6.58	-1.36	162	1%	0%	24%	164%	21%
Global Macro	0.26	0.79	3.04	-0.06	6.29	-12.06	-3.59	162	2%	0%	11%	247%	15%
Multi-Strategy	0.39	0.47	1.22	-1.31	6.73	-5.27	-1.74	159	0%	0%	10%	201%	11%
Emerging Markets	0.12	0.54	4.55	-0.76	7.98	-23.46	-7.33	162	10%	0%	7%	130%	5%
Fixed Income Arbitrage	0.19	0.20	1.04	-3.23	21.37	-7.47	-1.47	162	1%	0%	6%	490%	17%
Equity Market Neutral	0.60	0.47	0.79	0.20	3.66	-1.56	-0.78	162	1%	0%	5%	206%	6%
Managed Futures	0.08	0.28	3.43	0.01	3.26	-9.84	-5.19	162	1%	0%	5%	110%	3%
Convertible Arbitrage	0.32	0.41	1.29	-1.51	7.20	-5.19	-1.78	162	1%	0%	3%	231%	3%
Dedicated Short Bias	-0.09	-0.43	4.81	0.83	5.14	-9.20	-7.43	162	5%	0%	1%	222%	1%

Panel B: Other Institutions

							5th		Tests for Normality	
	Sharpe	Mean	Std Dev	Skew	Kurt	Min	Percenti	Obs	Pr(Skew)	Pr(Kurt)
Investment Banks	0.20	1.16	5.81	-0.59	4.93	-25.38	-7.53	161	0%	0%
Commercial Banks	0.21	1.07	5.04	-0.70	6.29	-24.00	-6.63	161	0%	0%
Insurance Companies	0.18	0.87	4.76	0.04	6.09	-16.55	-6.01	161	81%	0%
Market	0.15	0.65	4.19	-0.79	4.10	-16.20	-6.41	162	0%	3%

Table 2: q-Sensitivities

This table reports the matrix of bivariate q-sensitivities among the excess returns to ten Credit Suisse / Tremont hedge fund styles and the excess returns to other financial institutions (summary statistics are reported in Table 1). The sensitivities are calculated using quantile regressions (see Appendix A). Panel A reports the sensitivities from the 50%-quantile regression, Panel B reports the sensitivities from the 5%-quantile regression. Each cell of the table reports the sensitivity of a regression with the left hand side variable reported in the left column, and the right hand side variable reported in the top row.

Panel A: 50%-q-Sensitivities

	LSE	ED	GM	MS	EM	FIA	EMN	MF	CA	DSB	IB	CB	IC	M
Long/Short Equity (LSE)	100%	123%	35%	92%	36%	63%	108%	16%	70%	-38%	19%	28%	24%	30%
Event Driven (ED)	32%	100%	17%	38%	20%	55%	59%	6%	50%	-13%	6%	8%	7%	9%
Global Macro (GM)	48%	49%	100%	25%	26%	105%	80%	19%	40%	-3%	5%	11%	12%	12%
Multi-Strategy (MS)	16%	42%	4%	100%	7%	53%	50%	4%	47%	-4%	2%	1%	2%	3%
Emerging Markets (EM)	95%	187%	56%	79%	100%	98%	115%	2%	107%	-37%	21%	23%	25%	31%
Fixed Income Arbitrage (FIA)	9%	33%	7%	25%	6%	100%	38%	3%	42%	-1%	1%	2%	1%	1%
Equity Market Neutral (EMN)	13%	22%	8%	30%	8%	29%	100%	6%	24%	-3%	3%	5%	6%	5%
Managed Futures (MF)	18%	22%	36%	16%	1%	12%	40%	100%	-34%	0%	-5%	-10%	-3%	0%
Convertible Arbitrage (CA)	12%	44%	5%	31%	5%	65%	49%	-1%	100%	-3%	2%	3%	4%	3%
Dedicated Short Bias (DSB)	-131%	-172%	-19%	-12%	-46%	11%	-37%	0%	-58%	100%	-34%	-55%	-43%	-53%
Investment Banks (IB)	204%	281%	83%	59%	107%	84%	363%	-38%	177%	-125%	100%	128%	113%	129%
Commercial Banks (CB)	90%	190%	51%	-33%	38%	12%	165%	2%	8%	-44%	36%	100%	84%	80%
Insurance Companies (IC)	89%	114%	40%	-7%	24%	-7%	125%	6%	12%	-32%	24%	70%	100%	60%
Market (M)	140%	205%	49%	-4%	48%	62%	202%	0%	73%	-67%	55%	101%	89%	100%
HF Average Exposures	**32%**													
HF Average Value Weighted	**42%**													
IB+CB+IC Average Exposures	**42%**													

Panel B: 5%-q-Sensitivities

	LSE	ED	GM	MS	EM	FIA	EMN	MF	CA	DSB	IB	CB	IC	M
Long/Short Equity (LSE)	100%	119%	49%	20%	36%	34%	23%	-17%	23%	-24%	7%	31%	12%	34%
Event Driven (ED)	40%	100%	32%	70%	36%	104%	87%	-17%	95%	-20%	8%	18%	19%	18%
Global Macro (GM)	41%	115%	100%	122%	31%	114%	80%	-15%	50%	-8%	8%	7%	11%	7%
Multi-Strategy (MS)	13%	41%	18%	100%	-9%	58%	51%	-6%	74%	10%	-3%	-5%	-5%	3%
Emerging Markets (EM)	122%	213%	75%	-23%	100%	348%	97%	-50%	241%	-52%	17%	65%	48%	64%
Fixed Income Arbitrage (FIA)	19%	80%	26%	99%	9%	100%	59%	-3%	78%	-2%	1%	2%	3%	2%
Equity Market Neutral (EMN)	14%	39%	11%	37%	2%	41%	100%	2%	38%	-2%	2%	5%	3%	3%
Managed Futures (MF)	31%	140%	51%	151%	35%	132%	197%	100%	36%	16%	-11%	9%	3%	-11%
Convertible Arbitrage (CA)	28%	97%	33%	67%	15%	59%	122%	-10%	100%	-14%	10%	15%	18%	14%
Dedicated Short Bias (DSB)	-19%	16%	13%	41%	-9%	38%	10%	19%	43%	100%	-12%	4%	5%	-31%
Investment Banks (IB)	178%	435%	202%	135%	149%	328%	703%	-84%	349%	-118%	100%	117%	119%	130%
Commercial Banks (CB)	25%	132%	34%	65%	25%	235%	109%	-21%	113%	-53%	35%	100%	95%	79%
Insurance Companies (IC)	73%	121%	98%	-21%	45%	349%	309%	-57%	-14%	-40%	22%	73%	100%	56%
Market (M)	80%	248%	96%	155%	75%	249%	304%	-46%	187%	-81%	41%	113%	103%	100%
HF Average Exposures	**53%**													
HF Average Value Weighted	**66%**													
IB+CB+IC Average Exposures	**70%**													

Table 3: CoVaRs

This table reports the percentage increase of the five percent Value-at-Risk for the returns of the left column conditional on the fifth percentile of the returns of the top row relative to the unconditional 5% Value-at-Risk (reported in the first column). The Value-at-Risk is computed from the five percent pair wise quantile regressions (the slopes of these regressions are reported in Table 2). The p-values test the null hyothesis that average CoVaRs equal average VaRs and are generated via bootsrap with 200 draws.

	Unconditional VaR	**CoVaR percent increase**													
		LSE	ED	GM	MS	EM	FIA	EMN	MF	CA	DSB	IB	CB	IC	M
Long/Short Equity (LSE)	**-3.22**	**0**	69	68	0	79	48	37	-42	36	-124	84	76	33	84
Event Driven (ED)	**-1.36**	61	**0**	45	34	146	-7	75	-36	115	-93	118	122	76	118
Global Macro (GM)	**-3.59**	26	18	**0**	97	54	41	31	-11	33	-9	46	17	29	46
Multi-Strategy (MS)	**-1.33**	76	7	83	**0**	-22	77	81	31	224	96	-11	-6	-25	-11
Emerging Markets (EM)	**-7.33**	44	43	36	-17	**0**	81	24	-33	71	-77	61	67	46	61
Fixed Income Arbitrage (FIA)	**-1.51**	33	49	52	52	28	**0**	17	-16	95	-13	32	7	12	32
Equity Market Neutral (EMN)	**-0.78**	31	8	71	33	-1	53	**0**	33	77	-32	76	81	62	76
Managed Futures (MF)	**-5.19**	10	12	47	2	44	3	37	**0**	-3	14	-9	8	-27	-9
Convertible Arbitrage (CA)	**-1.78**	53	74	78	65	58	143	109	-42	**0**	-60	60	54	77	60
Dedicated Short Bias (DSB)	**-7.43**	-44	-24	2	8	-25	7	-20	6	-17	**0**	-22	-3	2	-22
Investment Banks (IB)	**-7.53**	42	62	59	57	74	63	84	-15	70	-95	**0**	71	82	0
Commercial Banks (CB)	**-6.63**	14	63	23	5	28	85	14	-12	23	-67	51	**0**	58	51
Insurance Companies (IC)	**-6.01**	24	42	37	-12	55	66	80	-67	-20	-52	47	58	**0**	**47**
Market (M)	**-7.53**	42	62	59	57	74	63	84	-15	70	-95	0	71	**82**	**0**
HF Average	**-3.35**						**30.57**		**p-value 0.0036**						
HF Weighted	**-2.77**						**35.48**		**p-value 0.0861**						
IB+CB+IC Average	**-6.72**						**32.41**								

Table 4: Quantile Granger Causality

This table reports the significance of five percent quantile regressions. In Columns A, the left hand side excess return is reported in the first column, and is regressed on its own lag, as well as the lagged excess return of the variable in the top row of columns A. The significance refers to the coefficient of the top row, * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level.

	A: Hedge Funds Forecasting Banks			B: Banks Forecasting Hedge Funds		
	I-Banks	C-Banks	Insur	I-Banks	C-Banks	Insur
Hedge Fund Index						
Long/Short Equity						
Event Driven						
Global Macro						
Multi-Strategy	**					
Emerging Markets						
Fixed Income Arbitrage	**					
Equity Market Neutral						
Managed Futures						
Convertible Arbitrage	**			*		
Dedicated Short Bias	***					

Table 5: Summary Statistics of Risk Factors

This table reports summary statistics for excess returns of six risk factors. The repo Treasury spread is the difference between the one month general collateral Treasury repo rate (from ICAP) and the one month Treasury bill rate (from Federal Reserve Board's H.15 releases). The 10 year - 3 month Treasury return is the return to the 10-year constant maturity Treasury bond (from H.15) in excess of the 3-month Treasury Bill. Moody's BAA - 10-year Treasury return is the return to Moody's BAA bond portfolio in excess of the return to the 10-year constant maturity Treasury return. The CRSP market excess return is in excess of the 3-month Treasury bill and is from the Center of Research in Security Prices. The VIX straddle return is computed from the Black-Scholes (1973) formula using CBOE's VIX implied volatility index, the return to the S&P500, and the 3-month Treasury rate. The variance swap return is the difference between realized S&P500 variance from daily closing data and the VIX implied variance. The tests for normality give the p-values of Royston's (1991) test that skewness / kurtosis are normal.

						5th	Tests for Normality		
	Mean	Std Dev	Skew	Kurt	Min	Percentil	Pr(Skew)	Pr(Kurt)	Obs
Repo - Treasury Rate	0.02	0.05	-0.85	6.04	-0.20	-0.06	50%	0%	162
10 Year - 3 Month Treasury Return	0.16	2.24	-0.34	2.73	-6.25	-3.67	7%	55%	162
Moody's BAA - 10 Year Treasury Return	0.24	2.36	-0.13	3.47	-7.47	-3.28	47%	18%	162
CRSP Market Excess Return	0.65	4.19	-0.79	4.10	-16.20	-6.41	0%	2%	162
VIX Straddle Excess Return	1.01	11.57	0.94	4.76	-24.63	-15.26	0%	0%	162
Variance Swap Return	-0.39	0.41	2.38	10.30	-0.86	-0.77	0%	0%	162

Table 6: Summary Statistics of Monthly Offloaded Returns

Panel A reports the summary statistics of excess returns as in Table 1 with CAPM and six factors alphas in addition. Panel B reports summary statistics for the offloaded returns relative to the six risk factors of Table 5. Offloaded returns are computed as pricing errors (constant plus residual) of the 5% quantile regression of returns on the six factor pricing model.

Panel A: Returns

	Sharpe	Mean	Std Dev	Skew	Kurt	Min	5th Percentile	Tests for Normality Pr(Skew)	Tests for Normality Pr(Kurt)	CAPM alpha	6-Factor alpha
Hedge Fund Index	0.27	0.58	2.17	-0.03	5.55	-7.98	-2.58	0%	0%	0.39 ***	-0.11
Event Driven	0.24	0.69	2.84	0.12	7.13	-11.86	-3.22	2%	97%	0.37 **	-0.11
Long/Short Equity	0.26	0.31	1.16	-1.31	10.30	-6.58	-1.36	31%	10%	0.22 ***	0.03
Fixed Income Arbitrage	0.26	0.79	3.04	-0.06	6.29	-12.06	-3.59	0%	3%	0.67 ***	0.10
Global Macro	0.39	0.47	1.22	-1.31	6.73	-5.27	-1.74	0%	1%	0.45 ***	0.50 ***
Multi-Strategy	0.12	0.54	4.55	-0.76	7.98	-23.46	-7.33	0%	0%	0.16	-0.09
Equity Market Neutral	0.19	0.20	1.04	-3.23	21.37	-7.47	-1.47	0%	0%	0.19 **	0.07
Emerging Markets	0.60	0.47	0.79	0.20	3.66	-1.56	-0.78	2%	97%	0.43 ***	0.59 ***
Convertible Arbitrage	0.08	0.28	3.43	0.01	3.26	-9.84	-5.19	31%	10%	0.34	-0.08
Managed Futures	0.32	0.41	1.29	-1.51	7.20	-5.19	-1.78	0%	3%	0.37 ***	0.40 **
Dedicated Short Bias	-0.09	-0.43	4.81	0.83	5.14	-9.20	-7.43	0%	1%	0.19	-0.19
Weighted average	**0.26**	**0.50**								**0.35**	**0.07**
Average	**0.24**	**0.37**								**0.34**	**0.12**
Investment Banks	0.12	1.16	9.77	-0.26	4.54	-34.65	-13.49	0%	3%		
Commercial Banks	0.21	1.07	5.11	-0.72	6.35	-24.14	-6.92	0%	1%		
Insurance Companies	0.18	0.87	4.87	0.07	6.10	-16.69	-6.65	0%	0%		
Market	0.15	0.65	4.25	-0.78	4.02	-16.20	-7.15	0%	3%		

Panel B: 5%-Risk Factor Offloaded Returns

	Sharpe	Mean	Std Dev	Skew	Kurt	Min	5th Percentile	Tests for Normality Pr(Skew)	Tests for Normality Pr(Kurt)	CAPM alpha	6-Factor alpha
Hedge Fund Index	0.19	0.35	1.86	0.66	4.76	-4.87	-2.35	0%	0%	0.30 **	-0.11
Event Driven	-0.26	-0.53	2.02	1.24	7.11	-5.01	-3.40	0%	0%	-0.56 ***	-0.11
Long/Short Equity	-0.08	-0.09	1.05	0.38	2.90	-2.49	-1.59	0%	3%	-0.04	0.03
Fixed Income Arbitrage	0.27	0.84	3.11	0.59	5.01	-9.44	-3.48	0%	1%	0.69 ***	0.10
Global Macro	0.76	1.06	1.40	-0.92	6.69	-6.23	-0.97	0%	0%	1.05 ***	0.50 ***
Multi-Strategy	0.18	0.74	4.13	-0.05	3.21	-10.32	-6.90	70%	54%	0.83	-0.09
Equity Market Neutral	-0.03	-0.03	1.10	-0.87	6.17	-5.50	-1.78	70%	58%	-0.02	0.07
Emerging Markets	1.17	1.01	0.87	0.57	3.53	-0.75	-0.25	51%	65%	1.00 ***	0.59 ***
Convertible Arbitrage	-0.07	-0.27	3.70	0.20	2.54	-8.43	-5.97	29%	28%	-0.31	-0.08
Managed Futures	0.34	0.47	1.39	-0.43	4.84	-5.40	-1.70	19%	0%	0.48 ***	0.40 **
Dedicated Short Bias	0.13	0.33	2.59	0.27	3.01	-6.42	-3.36	8%	39%	0.34 *	-0.19
Weighted average	**0.08**	**0.12**								**0.11**	**0.07**
Average	**0.24**	**0.35**								**0.35**	**0.12**
Investment Banks	-0.22	-0.79	3.55	0.87	5.56	-9.15	-6.11	0%	0%		
Commercial Banks	-0.36	-1.39	3.87	-0.08	5.54	-15.87	-6.25	0%	1%		
Insurance Companies	0.14	0.57	4.17	0.47	6.04	-14.86	-4.61	1%	0%		

Table 7: q-Sensitivities for Offloaded Returns

This table shows the bivariate cosensitivities from 5% quantile regressions of offloaded excess returns. In Panel A, offloaded returns are constructed as pricing errors from OLS regressions of the six factor pricing model. In Panel B, offloaded returns are constructed as pricing errors from 5% quantile regressions of the six factor pricing model.

Panel A: 5%-q-Sensitivities, OLS Risk Factor Offloaded

	LSE	ED	GM	MS	EM	FIA	EMN	MF	CA	DSB	IB	CB	IC	M
Long/Short Equity (LSE)	100%	-2%	26%	-5%	11%	14%	35%	11%	-8%	-21%	-1%	-1%	-1%	-17%
Event Driven (ED)	6%	100%	6%	-14%	7%	-2%	37%	2%	20%	-3%	1%	8%	3%	3%
Global Macro (GM)	32%	-24%	100%	130%	24%	125%	21%	22%	84%	39%	15%	-25%	9%	-18%
Multi-Strategy (MS)	33%	-43%	17%	100%	-14%	83%	84%	6%	69%	23%	11%	-19%	-10%	-13%
Emerging Markets (EM)	125%	143%	80%	-56%	100%	193%	334%	-41%	100%	-67%	48%	35%	17%	14%
Fixed Income Arbitrage (FIA)	19%	9%	28%	26%	8%	100%	33%	-13%	65%	-11%	11%	2%	6%	-1%
Equity Market Neutral (EMN)	8%	31%	12%	21%	-2%	2%	100%	5%	28%	3%	6%	7%	2%	2%
Managed Futures (MF)	32%	-35%	60%	86%	35%	-85%	214%	100%	-16%	-22%	-8%	1%	1%	-1%
Convertible Arbitrage (CA)	37%	97%	26%	57%	13%	115%	126%	-17%	100%	-32%	18%	17%	23%	-8%
Dedicated Short Bias (DSB)	-32%	-5%	4%	-29%	-17%	-58%	22%	5%	-67%	100%	26%	22%	13%	-2%
Investment Banks (IB)	-48%	33%	17%	-87%	12%	54%	-40%	-13%	60%	18%	100%	75%	53%	-35%
Commercial Banks (CB)	-65%	58%	-44%	-90%	1%	3%	47%	5%	-39%	18%	83%	100%	73%	-1%
Insurance Companies (IC)	-87%	-63%	19%	-80%	-29%	-4%	66%	1%	-5%	66%	44%	77%	100%	5%
Market (M)	-67%	-18%	-12%	-15%	2%	122%	-83%	-2%	-12%	-9%	5%	2%	-10%	100%
HF Average Exposures	**34%**													
HF Average Value Weighted	**36%**													
IB+CB+IC Average Exposures	**25%**													

Panel B: 5%-q-Sensitivities, 5%-Quantile Risk Factor Offloaded

	LSE	ED	GM	MS	EM	FIA	EMN	MF	CA	DSB	IB	CB	IC	M
Long/Short Equity (LSE)	100%	0%	0%	0%	6%	0%	0%	1%	0%	0%	0%	0%	-8%	0%
Event Driven (ED)	2%	100%	2%	0%	1%	0%	0%	4%	0%	0%	0%	4%	0%	0%
Global Macro (GM)	34%	-51%	100%	76%	13%	116%	0%	0%	26%	0%	0%	0%	12%	0%
Multi-Strategy (MS)	0%	0%	0%	100%	-5%	28%	112%	0%	16%	3%	0%	-6%	0%	0%
Emerging Markets (EM)	84%	68%	24%	0%	100%	85%	0%	0%	56%	-61%	0%	0%	16%	0%
Fixed Income Arbitrage (FIA)	17%	0%	16%	26%	9%	100%	0%	0%	61%	-5%	0%	0%	0%	0%
Equity Market Neutral (EMN)	0%	0%	6%	15%	-3%	0%	100%	2%	0%	0%	1%	3%	0%	0%
Managed Futures (MF)	0%	0%	17%	0%	0%	-12%	113%	100%	0%	-4%	0%	0%	0%	0%
Convertible Arbitrage (CA)	13%	27%	17%	41%	12%	70%	72%	0%	100%	0%	0%	-4%	0%	0%
Dedicated Short Bias (DSB)	-25%	-11%	0%	0%	0%	-12%	0%	0%	-59%	100%	23%	16%	14%	0%
Investment Banks (IB)	-32%	0%	0%	-16%	0%	0%	0%	0%	0%	0%	100%	49%	28%	0%
Commercial Banks (CB)	-68%	0%	-48%	-8%	-25%	0%	0%	0%	0%	13%	71%	100%	65%	0%
Insurance Companies (IC)	-62%	-121%	0%	0%	-9%	0%	0%	0%	-11%	56%	44%	64%	100%	0%
Market (M)	0%	-67%	32%	41%	0%	62%	0%	0%	48%	0%	11%	0%	-1%	100%
HF Average Exposures	**20%**													
HF Average Value Weighted	**26%**													
IB+CB+IC Average Exposures	**14%**													

Table 8: CoVaRs

This table reports the bivariate VaRs as in Table 3, but for the offloaded returns (as described in the caption of Table 7).

Panel A: CoVaR for OLS-offloaded returns

	Unconditional VaR	CoVaR percent increase													
		LSE	ED	GM	MS	EM	FIA	EMN	MF	CA	DSB	IB	CB	IC	M
Long/Short Equity (LSE)	**-2.98**	**0**	1	31	-4	18	5	12	14	2	-39	0	1	0	-31
Event Driven (ED)	**-1.42**	10	**0**	14	-20	39	0	24	8	24	-8	7	35	8	13
Global Macro (GM)	**-4.21**	26	-14	**0**	80	37	36	9	26	54	32	14	-16	11	-19
Multi-Strategy (MS)	**-1.82**	43	-52	20	**0**	-57	54	25	-4	55	57	30	-66	-62	-55
Emerging Markets (EM)	**-6.36**	67	35	68	-10	**0**	60	77	-18	32	-37	40	29	24	24
Fixed Income Arbitrage (FIA)	**-1.44**	49	1	88	31	43	**0**	19	-47	90	-26	31	6	27	-5
Equity Market Neutral (EMN)	**-0.69**	16	46	58	51	-14	4	**0**	20	46	14	36	29	16	22
Managed Futures (MF)	**-5.38**	21	-14	54	35	45	-14	49	**0**	-7	-18	-8	2	2	0
Convertible Arbitrage (CA)	**-1.51**	86	93	91	106	68	112	142	-44	**0**	-57	91	74	135	-18
Dedicated Short Bias (DSB)	**-4.40**	-25	-3	5	-15	-24	-25	8	4	-37	**0**	36	20	15	-3
Investment Banks (IB)	**-5.04**	-43	12	10	-38	16	15	-10	-6	19	11	**0**	23	32	-35
Commercial Banks (CB)	**-3.73**	-28	20	-30	-37	1	1	17	6	-20	22	110	**0**	79	-1
Insurance Companies (IC)	**-4.70**	-54	-10	11	-37	-29	-1	26	1	-2	51	42	63	**0**	**4**
Market (M)	**-7.22**	-19	0	-7	-3	2	35	-6	-1	-2	-8	3	2	**-11**	**0**
HF Average	**-3.02**							**19.59**		**p-value 0.0006**					
HF Weighted	**-2.74**							**15.53**		**p-value 0.0003**					
IB+CB+IC	**-4.49**							**11.18**							

Panel B: CoVaR for 5%-Quantile offloaded returns

	Unconditional VaR	CoVaR percent increase													
		LSE	ED	GM	MS	EM	FIA	EMN	MF	CA	DSB	IB	CB	IC	M
Long/Short Equity (LSE)	**-3.17**	**0**	0	0	0	8	0	0	1	0	0	0	0	-12	0
Event Driven (ED)	**-1.61**	1	**0**	4	0	4	0	0	14	0	0	0	11	0	0
Global Macro (GM)	**-3.44**	38	-12	**0**	56	31	46	0	0	21	0	0	0	26	0
Multi-Strategy (MS)	**-1.21**	0	0	0	**0**	-33	40	93	0	24	4	0	-37	0	0
Emerging Markets (EM)	**-6.98**	22	11	12	0	**0**	16	0	0	13	-49	0	0	7	0
Fixed Income Arbitrage (FIA)	**-1.80**	6	0	35	33	25	**0**	0	0	75	-14	0	0	0	0
Equity Market Neutral (EMN)	**-0.30**	0	0	67	67	-67	0	**0**	40	0	0	7	50	0	0
Managed Futures (MF)	**-5.86**	0	0	10	0	0	-4	19	**0**	0	-3	0	0	0	0
Convertible Arbitrage (CA)	**-1.80**	14	29	42	58	52	63	49	0	**0**	0	0	-4	0	0
Dedicated Short Bias (DSB)	**-4.22**	-17	-4	0	0	0	-7	0	0	-30	**0**	31	15	21	0
Investment Banks (IB)	**-6.06**	-12	0	0	-5	0	0	0	0	0	0	**0**	20	17	0
Commercial Banks (CB)	**-6.35**	-14	0	-18	-2	-23	0	0	0	0	7	49	**0**	47	0
Insurance Companies (IC)	**-5.23**	-24	-15	0	0	-11	0	0	0	-3	56	56	70	**0**	**0**
Market (M)	**-8.64**	0	-12	15	10	0	14	0	0	15	0	7	0	**0**	**0**
HF Average	**-3.04**							**9.02**		**p-value 0.1245**					
HF Weighted	**-2.77**							**6.32**		**p-value 0.1232**					
IB+CB+IC	**-5.88**							**4.47**							

Table 9: Flow-Performance Regressions

This table reports results of panel regressions over time and across strategies with time and strategy fixed effects. The left hand side variables are monthly flows relative to total flows in and out of the hedge fund sector. The right hand side variables are 1) past monthly returns, 2) past annual returns, 3) the annual rolling alpha, 4) the annual rolling Sharpe ratio, 5) the annual rolling standard deviation and 6) the expanding window six factor VaR computed as the predicted value from a 5% quantile regression on the six pricing factors with a minimum of 24 months of data (in sample for the first 24 months).

		(i)	(ii)	(iii)	(iv)	(iv)	(vi)	(vii)	(viii)	(ix)	(x)
Lagged											
Monthly Return	coeff.	0.05	0.04	0.05	0.05	0.04	0.04	0.05	0.05	0.04	0.05
	p-value	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***
Annual Return	coeff.	0.07	0.06	0.07			0.06	0.06		0.07	0.07
	p-value	0.00***	0.00***	0.00***			0.00***	0.00***		0.00***	0.00***
Alpha	coeff.	0.00							0.00	0.00	0.00
	p-value	0.48							0.60	0.39	0.34
Sharpe Ratio	coeff.	0.00				0.06	0.00	0.01			
	p-value	0.89				0.01**	0.88	0.83			
Standard Deviation	coeff.	0.00									
	p-value	0.89									
6-factor VaR	coeff.	0.00	0.00	0.00				0.00			0.00
	p-value	0.96	0.98	1.00				0.96			0.94

Table 10: Bivariate Expected Shortfall

This table reports the bivariate Expected shortfalls (ES) for total returns and for ES offloaded returns.

Panel A: ES conditional on strategies' uncond. ES

	Unconditional Expected Shortfall	Co-Expected Shortfall percent increase												
		LSE	ED	GM	MS	EM	FIA	EMN	MF	CA	DSB	IB	CB	IC
Long/Short Equity (LSE)	**-4.72**	**0**	43	81	-25	47	101	28	-65	32	-93	51	53	20
Event Driven (ED)	**-2.01**	73	**0**	92	73	89	78	95	-66	124	-77	91	80	78
Global Macro (GM)	**-5.62**	12	0	**0**	62	52	24	-8	-1	44	5	9	2	8
Multi-Strategy (MS)	**-2.68**	7	-37	43	**0**	-27	35	25	-21	121	45	-42	-40	-65
Emerging Markets (EM)	**-8.60**	71	57	69	-48	**0**	127	52	-38	104	-60	69	69	75
Fixed Income Arbitrage (FIA)	**-2.35**	0	8	63	86	24	**0**	-18	-52	106	2	2	-10	-9
Equity Market Neutral (EMN)	**-1.16**	36	38	56	43	1	36	**0**	10	41	-22	39	33	35
Managed Futures (MF)	**-6.56**	-5	-15	50	-31	24	0	38	**0**	-41	22	-10	-2	-34
Convertible Arbitrage (CA)	**-3.16**	16	25	37	29	9	78	35	-50	**0**	-38	15	17	32
Dedicated Short Bias (DSB)	**-7.92**	-34	-23	5	8	-26	4	-22	6	-5	**0**	-31	0	1
Investment Banks (IB)	**-10.03**	41	47	88	48	48	102	71	-36	83	-83	**0**	59	82
Commercial Banks (CB)	**-8.53**	39	58	67	-15	57	149	69	-30	80	-49	53	**0**	74
Insurance Companies (IC)	**-9.40**	24	20	51	-44	21	71	50	-37	15	-42	28	48	**0**
HF Weighted	**-3.99**						**28.64**							
IB+CB+IC Average	**-9.32**						**26.68**							

Panel B: ES conditional on uncond. ES, ES offloaded risk factors

	Unconditional Expected Shortfall	Co-Expected Shortfall percent increase												
		LSE	ED	GM	MS	EM	FIA	EMN	MF	CA	DSB	IB	CB	IC
Long/Short Equity (LSE)	**-3.90**	**0**	1	6	-5	3	1	0	0	0	2	-4	-3	-5
Event Driven (ED)	**-1.82**	3	**0**	4	4	11	1	7	7	1	3	3	8	-1
Global Macro (GM)	**-5.09**	12	-8	**0**	21	9	15	-6	-6	13	-5	-4	-5	4
Multi-Strategy (MS)	**-2.24**	9	19	31	**0**	-12	25	12	-6	29	-4	-8	-14	0
Emerging Markets (EM)	**-7.84**	10	5	7	0	**0**	10	2	0	9	-33	0	0	1
Fixed Income Arbitrage (FIA)	**-2.65**	19	-2	33	46	26	**0**	-2	-7	54	-8	7	-1	4
Equity Market Neutral (EMN)	**-0.51**	45	35	6	51	-25	14	**0**	14	12	20	8	14	16
Managed Futures (MF)	**-6.73**	1	3	3	2	2	-4	6	**0**	-6	2	-1	0	-2
Convertible Arbitrage (CA)	**-2.85**	22	11	14	14	11	36	7	-2	**0**	-39	-4	-11	0
Dedicated Short Bias (DSB)	**-4.52**	-31	-10	0	-7	-29	-17	0	-4	-47	**0**	25	21	18
Investment Banks (IB)	**-7.01**	-13	6	-2	-8	-4	3	-5	-4	-2	-2	**0**	37	23
Commercial Banks (CB)	**-10.08**	-19	-3	-10	-15	-20	0	15	7	-6	18	20	**0**	36
Insurance Companies (IC)	**-8.68**	-27	-19	-1	-20	-27	-10	13	28	-29	47	32	48	**0**
HF Weighted	**-3.51**						**5.94**							
IB+CB+IC Average	**-8.59**						**2.18**							

Table 11: CoVaRs on HFR Indices

This table reports the bivariate VaRs as in Tables 3 and 8, but with Indices from HFR.

Panel A: CoVaR

	Unconditional VaR	**Bivariate VaR**													
		EH	ED	MA	FI	EM	FIA	EMN	FID	CA	ENH	IB	CB	IC	M
HFRI Equity Hedge (EH)	**-2.44**	**0**	42	70	79	66	8	0	1	101	26	52	61	62	52
HFRI Event-Driven (ED)	**-1.48**	46	**0**	86	142	119	40	38	34	183	128	180	166	107	180
HFRI Macro (MA)	**-2.23**	41	70	**0**	59	82	2	20	51	36	52	29	22	35	29
HFRI Fixed Income (FI	**-0.66**	94	95	138	**0**	68	70	76	76	186	147	114	58	0	114
HFRI Emerging Markets (EM)	**-5.50**	53	57	56	77	**0**	11	-13	3	73	105	90	88	60	90
HFRI Fixed Income Arbitrage (FIA	**-1.18**	7	44	43	95	30	**0**	3	37	0	7	0	-8	-40	0
HFRI Equity Market Neutral Index (EMN)	**-0.65**	72	62	83	77	71	48	**0**	112	57	85	74	69	69	74
HFRI Fixed Income Diversified (FID	**-1.05**	50	51	48	45	46	2	45	**0**	25	0	0	-20	-20	0
HFRI Convertible Arbitrage (CA)	**-1.17**	62	114	56	95	66	105	94	13	**0**	120	62	56	68	62
HFRI Equity Non-Hedge (ENH)	**-5.05**	23	46	71	90	67	3	-11	0	82	**0**	42	64	80	42
Investment Banks (IB)	**-7.53**	31	47	51	72	63	40	-6	19	64	29	**0**	71	82	0
Commercial Banks (CB)	**-6.63**	14	54	15	50	67	10	30	27	21	16	51	**0**	58	51
Insurance Companies (IC)	**-6.01**	11	38	32	35	50	-4	47	53	9	60	47	58	**0**	**47**
Market	**-7.53**	31	47	51	72	63	40	-6	19	64	29	0	71	**82**	**0**
HF Average	**-2.14**							**53.31**							
IB+CB+IC Average	**-6.72**							**42.99**							

Panel B: CoVaR for 5%-Quantile offloaded returns

	Unconditional VaR	**Bivariate VaR**													
		EH	ED	MA	FI	EM	FIA	EMN	FID	CA	ENH	IB	CB	IC	M
HFRI Equity Hedge (EH)	**-1.22**	**0**	27	40	28	9	5	4	1	2	24	-5	-10	-17	0
HFRI Event-Driven (ED)	**-1.25**	25	**0**	30	5	26	0	10	2	32	38	0	0	-6	0
HFRI Macro (MA)	**-2.46**	28	0	**0**	0	20	0	0	0	0	17	0	0	0	0
HFRI Fixed Income (FI	**-0.64**	11	70	6	**0**	106	84	44	86	16	11	0	0	-6	0
HFRI Emerging Markets (EM)	**-4.49**	42	49	43	56	**0**	58	0	0	5	56	42	0	0	0
HFRI Fixed Income Arbitrage (FIA	**-1.46**	0	43	0	77	73	**0**	0	32	0	0	0	0	-11	0
HFRI Equity Market Neutral Index (EMN)	**-1.15**	14	0	0	0	-1	0	**0**	0	0	0	0	0	10	0
HFRI Fixed Income Diversified (FID	**-1.33**	7	1	7	21	0	0	2	**0**	0	4	0	0	0	0
HFRI Convertible Arbitrage (CA)	**-0.94**	56	87	85	100	106	0	0	0	**0**	79	0	0	0	0
HFRI Equity Non-Hedge (ENH)	**-1.97**	37	9	15	0	0	0	0	0	0	**0**	0	-8	-9	0
Investment Banks (IB)	**-6.06**	-12	0	-6	0	0	6	0	0	0	-10	**0**	20	17	0
Commercial Banks (CB)	**-6.35**	-30	-2	-30	0	-13	0	-2	0	0	-45	49	**0**	47	0
Insurance Companies (IC)	**-5.23**	-41	-26	0	-3	-13	-3	0	0	-8	-52	56	70	**0**	**0**
Market	**-8.64**	22	0	0	26	2	39	0	-13	13	7	7	0	**0**	**0**
HF Average	**-1.69**							**19.69**							
IB+CB+IC Average	**-5.88**							**0.20**							

Table 12: CoVaRs on Altvest Indices

This table reports the CoVaRs as in Tables 3 and 8, but with Indices from Altvest.

Panel A: CoVaR

	Unconditional VaR	**Bivariate VaR**													
		LSE	RV	EM	ED	SS	MA	CSA	DS	MA	CU	IB	CB	IC	M
Long/Short Equity (LSE)	**-1.53**	**0**	49	61	20	48	46	46	51	32	15	32	29	29	32
Relative Value (RV)	**-0.36**	183	**0**	175	114	81	133	144	111	103	106	114	81	125	114
Emerging Markets (EM)	**-2.22**	151	80	**0**	41	36	30	96	35	55	38	46	59	54	46
Event Driven (ED)	**-0.85**	221	160	201	**0**	94	109	226	113	132	49	175	149	84	175
Short Selling (SS)	**-2.90**	194	169	118	119	**0**	111	193	113	148	37	138	160	121	138
Macro (MA)	**-2.57**	51	40	39	19	16	**0**	12	42	7	23	28	21	12	28
Capital Structure Arbitrage (CSA)	**-0.75**	172	100	123	95	53	120	**0**	43	105	55	84	68	73	84
Distressed Securities (DS)	**-1.12**	258	224	140	56	117	93	172	**0**	140	61	75	55	78	75
Merger Arbitrage (MA)	**-0.89**	156	184	179	61	101	102	119	88	**0**	82	127	133	97	127
Currency (CU)	**-1.35**	36	32	84	56	57	48	98	64	68	**0**	72	69	46	72
Investment Banks (IB)	**-7.53**	80	77	47	51	52	42	55	65	73	42	**0**	71	82	0
Commercial Banks (CB)	**-6.63**	56	16	28	34	55	4	21	50	73	38	51	**0**	58	51
Insurance Companies (IC)	**-6.01**	59	6	20	52	44	11	-19	43	39	22	47	58	**0**	**47**
Market (M)	**-7.53**	80	77	47	51	52	42	55	65	73	42	0	71	**82**	**0**
HF Average	**-1.47**							**85.78**							
IB+CB+IC Average	**-6.72**														

Panel B: CoVaR for 5%-Quantile offloaded returns

	Unconditional VaR	**Bivariate VaR**													
		LSE	RV	EM	ED	SS	MA	CSA	DS	MA	CU	IB	CB	IC	M
Long/Short Equity (LSE)	**-0.95**	**0**	54	33	31	47	3	21	2	59	0	0	0	0	0
Relative Value (RV)	**-0.46**	72	**0**	26	63	24	37	61	20	91	11	0	0	0	0
Emerging Markets (EM)	**-1.66**	21	50	**0**	9	20	27	11	14	4	2	0	0	0	0
Event Driven (ED)	**-0.83**	25	27	16	**0**	69	43	61	39	107	10	0	0	0	0
Short Selling (SS)	**-5.47**	17	22	11	31	**0**	27	0	20	37	0	31	26	0	0
Macro (MA)	**-1.75**	0	0	33	0	0	**0**	13	0	0	46	0	0	0	0
Capital Structure Arbitrage (CSA)	**-0.51**	96	169	67	129	0	90	**0**	49	112	0	0	0	0	0
Distressed Securities (DS)	**-1.22**	0	59	55	32	49	25	46	**0**	0	0	0	-7	-19	0
Merger Arbitrage (MA)	**-1.21**	25	31	7	30	39	10	17	6	**0**	7	0	0	7	0
Currency (CU)	**-1.60**	0	2	0	0	0	3	0	0	0	**0**	0	5	0	0
Investment Banks (IB)	**-6.06**	0	0	0	0	0	-3	0	0	0	0	**0**	20	17	0
Commercial Banks (CB)	**-6.35**	0	-7	-31	-2	0	-31	-26	-1	0	0	49	**0**	47	0
Insurance Companies (IC)	**-5.23**	0	-36	-34	-22	0	-24	-21	-27	-37	0	56	70	**0**	**0**
Market (M)	**-8.64**	-9	29	2	0	0	24	0	4	0	1	7	0	**0**	**0**
HF Average	**-1.32**							**26.20**							
IB+CB+IC Average	**-5.88**														