Hedge Fund Tail Risk*

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This Version: August 19, 2011
First Version: July 28, 2007

Abstract

This paper uses quantile regressions to document the increase in tail sensitivities between hedge funds in times of crisis. We identify seven factors that explain this tail dependence and show that offloading the risk associated with them significantly reduces spillover effects. However, we also show that it is costly for hedge funds to offload tail risk in terms of returns and flows.

Keywords: Financial Intermediation, Hedge Funds, Tail Risk

JEL classification: G10, G12

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*The authors would like to thank René Carmona, Xavier Gabaix, Beverly Hirtle, John Kambhu, Burton Malkiel, Maureen O'Hara, Matt Pritsker, José Scheinkman, Kevin Stiroh and seminar participants at Columbia University, Princeton University, Cornell University, Rutgers University, and the Federal Reserve Bank of New York for helpful comments. Brunnermeier acknowledges financial support from the Alfred P. Sloan Foundation.

The views expressed in this paper are those of the authors and do not necessarily represent those of the Federal Reserve Bank of New York or the Federal Reserve System.

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1 Introduction

Our financial architecture has undergone dramatic changes in recent years as market based financial institutions have gained ever more importance in the allocation of capital and credit. The hedge fund sector has become one of the key parts of the market based financial system, supporting liquidity provision and price discovery across financial markets. While hedge funds are liquidity providers in usual times, during times of market crisis, they can be forced to delever, potentially contributing to market volatility. The extent to which various hedge fund strategies are exposed to the tail risk that occurs during market turmoil is important to understand for risk management and financial stability purposes. This paper provides a framework for understanding the tail risk exposures of hedge fund strategies in more detail.

The recent global financial crisis provides several examples of large hedge fund failures. The beginning of the crisis in June 2007 was marked by the failure of two highly levered structured credit hedge funds owned by Bear Stearns. Subsequently, in March 2008—less than two weeks prior to Bear Stearns' failure—the Carlyle Capital Corporation, another highly levered fixed income hedge fund, declared bankruptcy due to margin calls. In addition, the hedge fund sector as a whole experienced severe losses following the failure of Lehman Brothers in September 2008.

During the financial crisis, distress spread across institutions due to liquidity spirals. In a liquidity spiral, initial losses in some asset classes force levered investors to reduce their positions, which leads to additional mark-to-market losses and potential spillovers to other asset classes. Importantly, margins and haircuts widen at the same time, forcing levered investors to reduce their leverage ratio. (Brunnermeier and Pedersen (2009)). As such, banks and prime brokers with large credit risk exposures to hedge funds may suffer potentially large losses if many hedge funds experience distress at the same time. From a financial stability point of view, it is therefore important to understand the degree to which different hedge fund strategies tend to experience simultaneous large losses.

In this paper, we use quantile regressions to empirically study the interdependencies between different hedge fund styles in times of crisis. We find that tail sensitivities between different strategies are higher in times of distress, suggesting the potential for simultaneous losses across many hedge funds. Furthermore, we identify seven risk factors that are related to these tail dependencies and show that offloading this risk significantly reduces the sensitivities where we define offloaded returns as the residuals obtained from regressing the raw returns on the seven risk factors. However—consistent with existing literature—we also find that these factors explain a large part of hedge funds' expected returns, and we provide some evidence suggesting that capital flows across strategies and over time reward those that load more heavily on the tail risk factors. Consequently, while offloading would be beneficial for a fund manager in the sense that it would reduce his exposure to tail risk, managers face strong incentives to load on tail risk factors as they tend to increase both the incentive fee (calculated as a percentage of the fund's profit) as well as their management fee (calculated as a percentage of total assets under management).

Related Literature. 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 (2008) 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 strategies 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 this increase in correlation since 2003 is due to a reduction in volatility—phenomenon that occurred across many financial assets—rather than to an increase in covariance. Dudley and Nimalendran (2010) present an empirical analysis of the liquidity spiral associated with margin increases in futures exchanges. The methods used in this paper to analyze the tail risk exposures of hedge funds to risk factors have also been used in Adrian and Brunnermeier (2009). However, while Adrian and Brunnermeier (2009) focus on the quantification of systemic risk of each financial institutions, the current paper focuses on the hedging of tail risk, not quantifying systemic risk.

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 (2009) 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, a large and growing number of papers 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.

In Section 2, we study the tail dependencies between hedge fund strategies in normal times and during crises. In Section 3, we estimate a risk factor model for the hedge fund returns and show that tail risk factors explain a large part of the dependencies between the strategies. We also study the incentives hedge funds face in taking on tail risk. Finally, Section 4 concludes.

2 q-Sensitivities

In this section, we examine the pairwise dependence of returns between hedge fund styles. We find that these dependencies are significantly higher in times of stress. We call these dependencies among hedge funds in times of stress "$q-$sensitivities", because we use quantile regressions to estimate them. The q stands for the tail quantile for which the dependence is estimated.

2.1 Hedge Fund Return Data

As private investment partnerships that are largely unregulated, hedge funds are more challenging to analyze and monitor than other financial institutions such as mutual funds, banks, or insurance companies. Only very limited data on hedge funds are made available through regulatory filings and, consequently, most studies rely on self-reported data.[1] We follow this approach and use the hedge fund style indices compiled by Credit Suisse/Tremont.

Several papers have compared the self-reported returns of different vendors (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

[1] 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.

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, while hedge fund return indices are certainly not ideal, they are still the best data available and their study is useful. Moreover, Malkiel and Saha (2005) provide evidence that the Credit Suisse/Tremont indices appear to be the least affected by various biases.

[Table 1]

Table 1 displays summary statistics of monthly excess returns for the ten hedge fund style indices included in the Credit Suisse/Tremont data over the period January 1994-November 2009. 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 order of their average weights in the overall index, calculated over the entire sample period. These weights are determined by the proportion of total assets under management in the hedge fund sector dedicated to each strategy, and the average values are reported in the last column of Table 1. We also report summary statistics of monthly excess returns for the overall hedge fund index, as well as for the CRSP equity market excess return, which we sometimes interpret as a proxy for a well-diversified mutual fund. The cumulative returns to the overall hedge fund index and the market are shown in Figure 1.

[Figure 1]

Table 1 shows that, while there is a wide disparity of Sharpe ratios across different strategies, the Sharpe ratio of the overall hedge fund index (0.21) is more than twice the Sharpe ratio of the market (0.09). Since hedge funds invest part of their wealth in highly illiquid instruments with stale or managed prices, they are able to smooth their returns and manipulate Sharpe ratios (see e.g. Asness, Krail, and Liew (2001) and Getmansky, Lo, and Makarov (2004)). The summary statistics also show that the hedge fund index has less negative skewness than the market return (-0.27 versus -0.86) and higher kurtosis (5.26 versus 4.43). With the exception of Managed Futures, normality is rejected on the basis of either skewness or kurtosis for all hedge fund styles. Thus, consistent with previous findings, the returns to hedge funds have both skewed and fat-tailed returns relative to normality.

2.2 Quantile Regressions

In this section, we use bivariate quantile regressions to analyze the tail sensitivities between different hedge fund strategies. Quantile regressions were developed by Koenker and Bassett (1978) and Bassett and Koenker (1978), and a literature review can be found in Koenker (2005).

Consider the q-percent quantile regression of strategy i's returns on strategy j's returns:

$$R_t^i = \alpha_q^{ij} + \beta_q^{ij} R_t^j + \varepsilon_t^{ij} \tag{1}$$

To study the tail dependence of strategy i with respect to strategy j, we extract the β_q^{ij} from Equation 1.

Definition 1 *We denote the* q-sensitivity *of strategy i with respect to strategy j as the coefficient β_q^{ij} from the q-percent bivariate quantile regression of strategy i's excess returns on strategy j's excess returns.*

Our definition of the q-sensitivity captures the degree to which the tail returns of strategy i comoves with the returns of strategy j. By varying the quantile q, we can analyze how the dependencies between hedge fund strategies change between normal times ($q = 50$) and times of crisis (e.g., $q = 5$).

Note that quantile regressions lend themselves to an easy method of calculating the Value-at-Risk (VaR), which we use later in Section 3.4. In particular, the 5% quantile of strategy i's return provides a direct estimate of (the negative of) its VaR. Adrian and Brunnermeier (2009) use this property of quantile regressions to generate a novel measure of systemic risk, CoVaR, which they define as the VaR of the financial sector conditional on a particular institution being in distress.

Table 2 reports the 50%- and 5%-sensitivities calculated from bivariate quantile regressions among the ten hedge fund strategies. For each strategy i, we calculate its q-sensitivity with respect to each of the nine other strategies, and then average to obtain a single 50%–and 5% sensitivity. For each strategy, we also calculate the percent change in the average 5%-sensitivity relative to the 50%, along with its p-value.

[Table 2]

Table 2 shows that average hedge fund sensitivities increase in the tails of the return distribution. For all the strategies, except for Dedicated Short Bias, the average 5%–sensitivity is higher than the 50% sensitivity, with the difference statistically significant in five cases. The last row in Table 2 reports the sensitivities weighted by their average weight in the overall index over this period. By this measure, we find that average sensitivities are nearly 50% higher in times of stress compared to normal times, indicating higher dependence between strategies and the potential for simultaneous losses during a crisis. The increase in sensitivities among hedge fund styles in times of stress has previously been noted by Boyson, Stahel, and Stulz (2008).

3 Identifying Tail Factors

Having established that sensitivities between hedge fund styles increase during times of stress, in this section we identify factors that explain this tail dependence. We define offloaded returns as the residuals obtained from regressing the raw returns on the seven risk factors. We argue that the factor structure explains this tail dependence if the sensitivities of the offloaded returns are much lower than those of the raw returns.

We begin by outlining our seven risk factors, and then create offloaded returns for each of the hedge fund styles as well as for the financial institution indices. We then generate *50%*- and *5%*-sensitivities using these offloaded returns.

3.1 Tail Factors - Description and Data

We select the following seven factors to try to capture the increase in tail dependence among hedge fund strategies. All seven factors have solid theoretical foundations and are included to capture certain aspects of risk. Moreover, they are also all liquid and easily tradable. Our factors are:

(i) the Center for Research in Security Prices (CRSP) *market return* in excess of the 3-month bill rate;

(ii) the *VIX straddle excess return* to capture the implied future volatility of the stock market. The VIX is from the CBOE, we get a tradable excess return series by calculating the hypothetical at-the-money straddle return that is based on the VIX implied volatility, and then subtract the 3-month bill rate.

(iii) the *variance swap return* to capture the associated risk premium for shifts in volatility. The variance swap contract pays the difference between the realized variance over the coming month and its delivery price at the beginning of the month.

Since the delivery price is not observable over our whole sample period, we use - as is common practice - the VIX squared, normalized to 21 trading days, i.e., $\left(\frac{VIX*21}{360}\right)^2$. The realization of the index variance is computed from daily S&P 500 Index data for each month. Note that, since the initial price of the swap contract is zero, returns are automatically expressed as excess returns.

(iv) a short-term *"liquidity spread"*, defined as the difference between the 3-month general collateral repo rate and the 3-month bill rate. We use the 3-month repo rate available on Bloomberg and obtain the 3-month Treasury rate from the Federal Reserve Bank of New York.

(v) the *carry-trade excess return* is calculated using the Deutsche Bank carry USD total return index. The index is constructed from a carry strategy on the G10 currencies that is rolled over quarterly. The index is long the three highest-yielding currencies and short the three lowest-yielding currencies.

(vi) the *slope of the yield curve*, measured by the yield spread between the 10-year Treasury rate and the 3-month bill rate from the Federal Reserve Board's H.15 release.

(vii) the *credit spread* between BAA rated bonds and the Treasury rate (with same maturity of 10 years) from the Federal Reserve Board's H.15 release.

All data are monthly from January 1994 through November 2009. Summary statistics are presented in Table 3.

[Table 3]

3.2 Offloaded Returns

Having specified our factors, we generate offloaded returns and study their effect on the q-sensitivities. In particular, we look at quantile offloaded returns—i.e., the residuals to the 5%-quantile regression of raw returns on our seven factors. More formally, we define offloaded returns in the following way.

Definition 2 *Consider the $q\%-$quantile regression of hedge fund strategy i onto a vector of tail risk factors X_t:* $R_t^i = \alpha_q^{iX} + \beta_q^{iX} X_t + \varepsilon_t^{iX}$

Offloaded returns $\tilde{R}_t^i$ are then defined as $\tilde{R}_t^i = R_t^i - \beta_q^{iX} X_t$

Monthly raw and offloaded returns for the ten hedge fund strategies, as well as for the overall index, are plotted in Figure 2. In most cases, offloading the risk associated with our factors reduces the volatility of the monthly returns.

[Figure 2] [Table 4]

Table 4 displays the summary statistics for these offloaded returns. Comparing to Table 1, we see that offloading tail risk markedly reduces the weighted average mean return and Sharpe ratio of the ten hedge fund strategies (and the difference is statistically significant). Looking at individual styles, some offloaded mean returns and Sharpe ratios even enter negative territory. The kernel densities in Figure 3 reveal that offloading reduces the fat left tail of the overall index, while having little effect on the right tail.

[Figure 3]

Table 5 compares the CAPM-α's of the total and offloaded returns for the hedge fund strategies. We see that the α's drop notably after offloading the risk associated with our factors; the weighted average α declines from 0.40 to 0.13. Note that we take the simple average of α's rather than the average of the absolute value of the α's since it is not easy to short a hedge fund style.

[Table 5]

3.3 q-Sensitivities of Offloaded Returns

As we did for the raw returns in Section 2, we replicate the bivariate 5%-quantile regressions for the offloaded returns. That is, we quantile regress the offloaded returns of style i on the offloaded returns of style j and calculate the average 5%-sensitivity for each strategy. Table 6 compares the average 5%-sensitivities calculated using total and offloaded returns, and also displays the percent change of the offloaded sensitivities relative to the total along with their p-value.

[Table 6]

Table 6 shows that, with the exception of only three strategies, using offloaded returns unequivocally decreases the 5%-sensitivity by a statistically significant margin. In fact, the weighted average shows that offloading the tail risk reduces the 5%-sensitivity by more than 75%. Figure 4 confirms these results by plotting the weighted average q-sensitivity across the hedge fund styles for all q between 5 and 95. We see that the q-sensitivity of the offloaded returns are generally well below that of the raw returns:

[Figure 4]

Beyond looking at sensitivities across states of the world (i.e., for different values of q), we can also investigate their evolution over time. To do so, we estimate a multivariate BEKK-ARCH(2) model and extract the evolution of covariances across the ten strategies over time. The average of these covariances is shown in Figure 5.

[Figure 5]

The average covariance of the offloaded returns is markedly less volatile than that of the total returns. While the average covariance of total returns spiked during the LTCM crisis in the third quarter of 1998, in January 2000, and, most dramatically, following the bankruptcy of Lehman Brothers in September 2008, the average covariance of the offloaded returns increased much less during the same periods.

These results strongly suggest that interdependencies between different hedge fund styles could be significantly reduced were funds to offload the tail risk associated with our seven factors. From a financial stability point of view, this is desirable as it would reduce the potential for simultaneous losses across many strategies during a crisis. However, it is possible that individual fund managers face no such incentive to offload tail risk. We investigate this in the following section.

3.4 Incentives to Load on Tail Risk

Because our seven factors were chosen to be tradable and highly liquid, it would be possible for hedge fund managers to offload the associated risk without incurring large trading costs. Consequently, offloading is α-neutral within our model. However, as noted previously in our comparison of Tables 1 and 4, offloading this risk significantly reduces the weighted average monthly return of the hedge funds from 0.51 to 0.08. In other words, a large proportion of hedge funds' outperformance relative to the market index appears to be a direct result of their loading on these "tail" factors. Consequently, the question arises whether hedge fund managers have any incentive to offload this risk, when doing so would lower their expected return.

Fund managers are typically paid a performance fee of 20% of the realized profits plus 2% of the value of total assets under management. As such, though offloading tail risk lowers the manager's expected compensation via the performance fee, the expected compensation via the management fee may actually be higher if offloading risk leads to increased inflows into the fund.

To investigate this, we study these flows and compare the effects of average returns and various risk measures on flows across strategies and over time. We use the weights of each strategy within the overall hedge fund index to generate a measure of relative flow—i.e., the flow into strategy i is expressed as a proportion of total flow into the hedge fund sector. Recall that w_t^i, the weight of strategy i in the overall index, is determined according to the proportion of total hedge fund assets under management dedicated to funds operating under strategy i. Our flow measure is accordingly defined as

$$flow_{t+1}^i = w_{t+1}^i - w_t^i \left(\frac{1 + r_{t+1}^i}{1 + r_{t+1}^{index}} \right), \tag{2}$$

where r_{t+1}^i and r_{t+1}^{index} are the monthly returns to strategy i and the overall index, respectively. Consequently, our flow variable adjusts changes in the relative weights of each strategy between t and $t+1$ by the return of each strategy relative to the index return.

[Table 7]

Table 7 shows that, as expected, flows are very sensitive to past monthly and annual returns. However, we find that taking on more risk, as indicated by higher *VaR*s, is also associated with larger future flows. This indicates that offloading tail risk not only reduces hedge fund managers' expected compensation via their performance fee (through lower expected returns), but also punishes them with lower management fees by reducing inflows. Consequently, while offloading the risk associated with our factors may be highly desirable from a systemic risk point of view, individual managers have no incentive to do so and, in fact, seem to be rewarded for loading more heavily on these tail risk factors.

4 Conclusion

Our paper documents that sensitivities between hedge fund styles increase in the tails, leading to the potential for simultaneous large losses across different strategies. We identify seven factors that can account for this increase in tail dependence in times of crisis, and show that offloading the risk associated with them greatly reduces the sensitivities between hedge fund styles as well as between different financial institutions. However, offloading tail risk might come at the cost of lower compensation for individual hedge fund managers.

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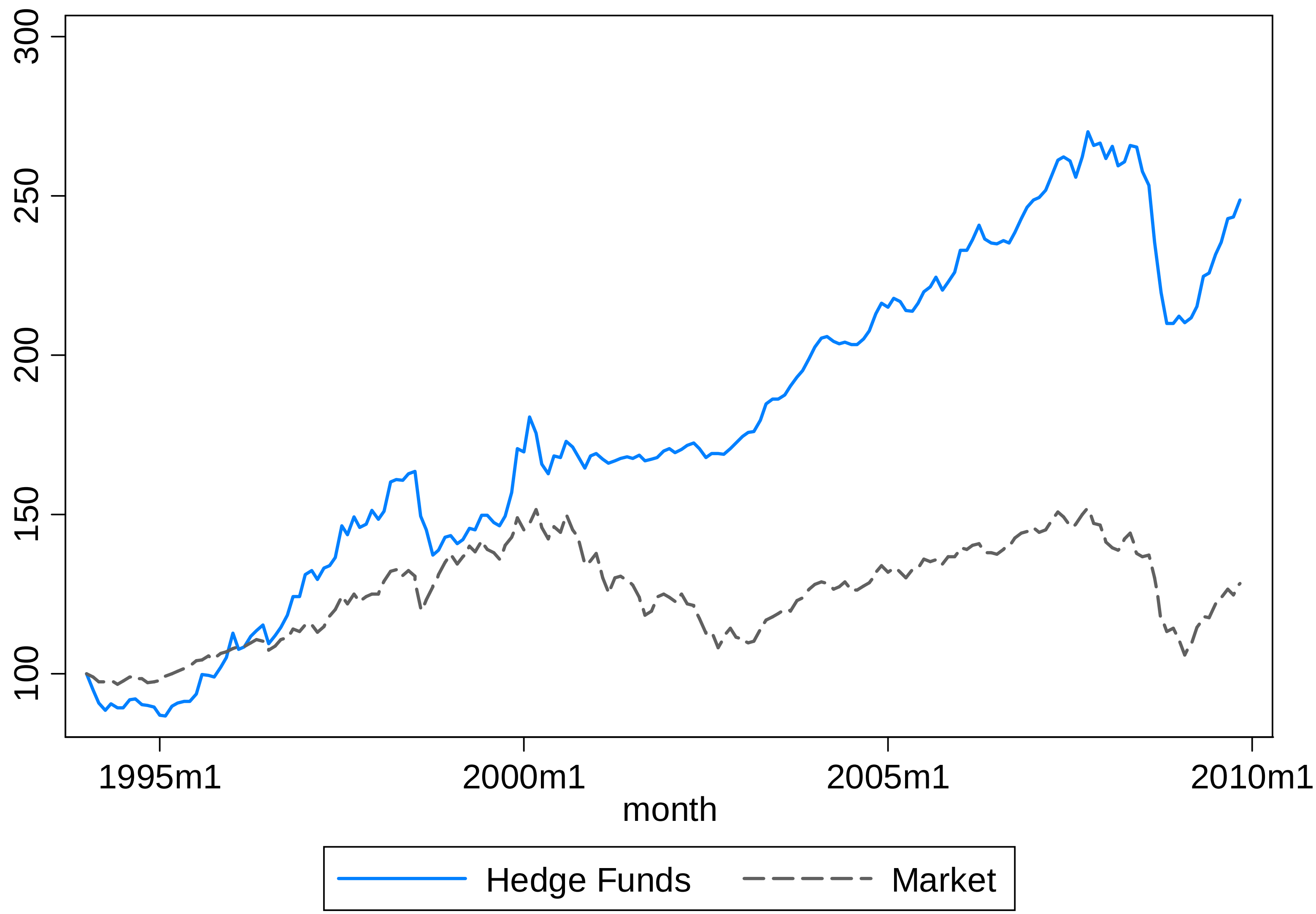

Figure 1: Cumulative Returns. This figure plots cumulative returns for the overall Credit Suisse/Tremont hedge fund index and for the market over the period from January 1994 through November 2009. The market return is the cum dividend value-weighted CRSP return.

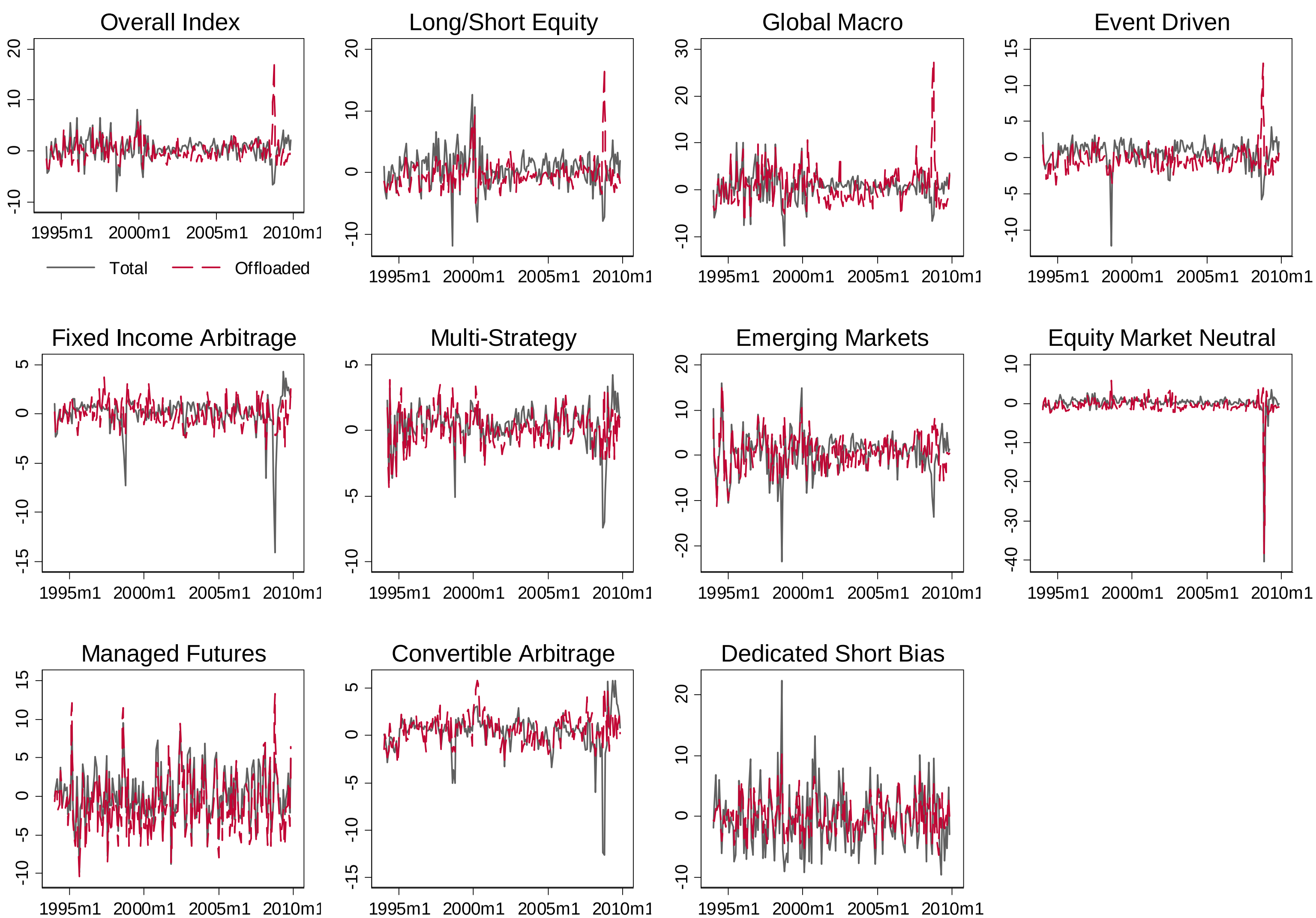

Figure 2: Monthly Total and Offloaded Excess Returns. This figure plots monthly total and 5%-quantile offloaded returns for the ten Credit Suisse/Tremont hedge fund strategies as well as for the overall index. Offloaded returns are calculated as the residuals from 5%-quantile regressions of total excess returns on the seven risk factors.

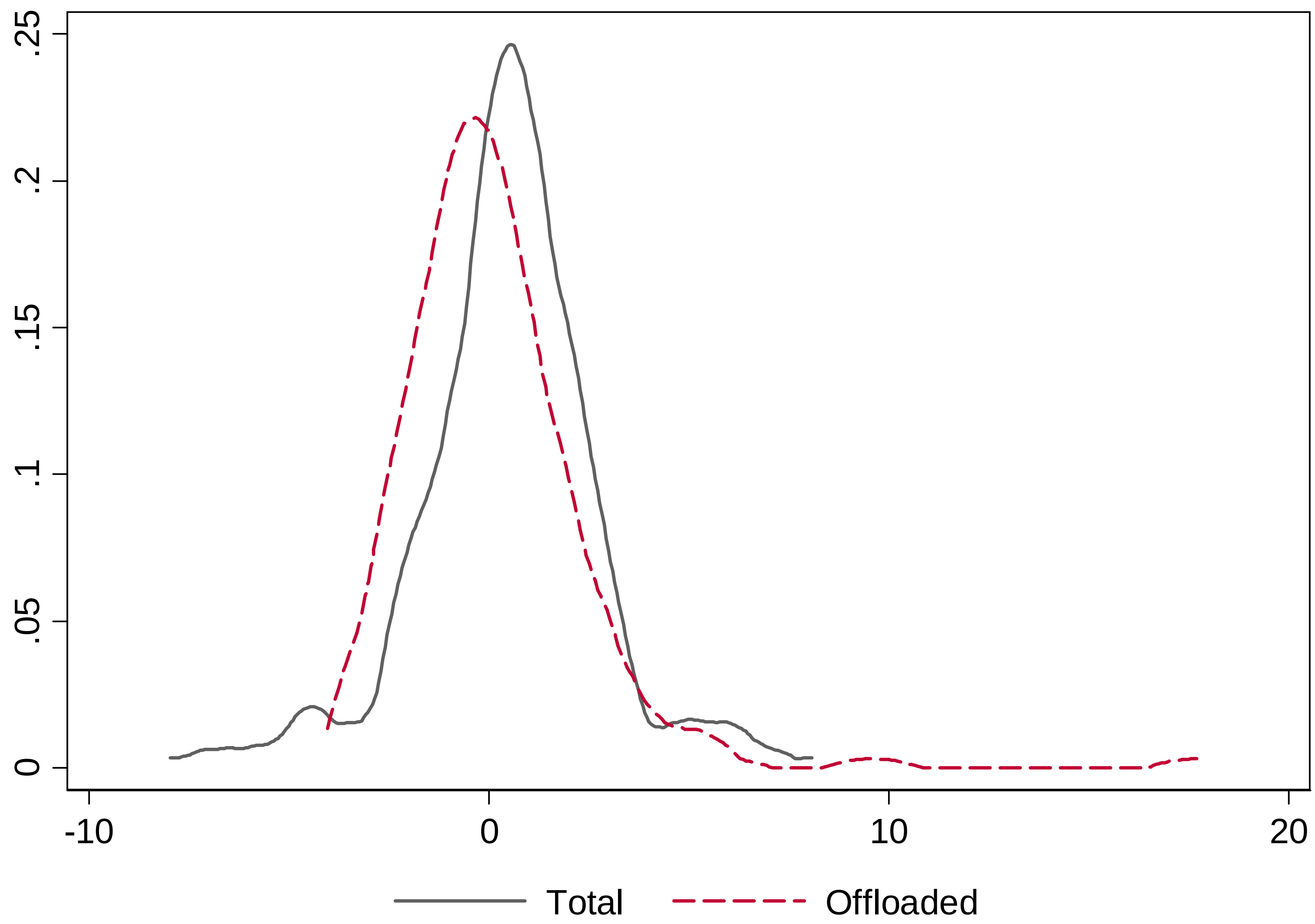

Figure 3: Kernel Densities of Total and Offloaded Returns. This figure plots the kernel densities of the total and 5%-quantile offloaded returns for the overall Credit Suisse/Tremont hedge fund index.

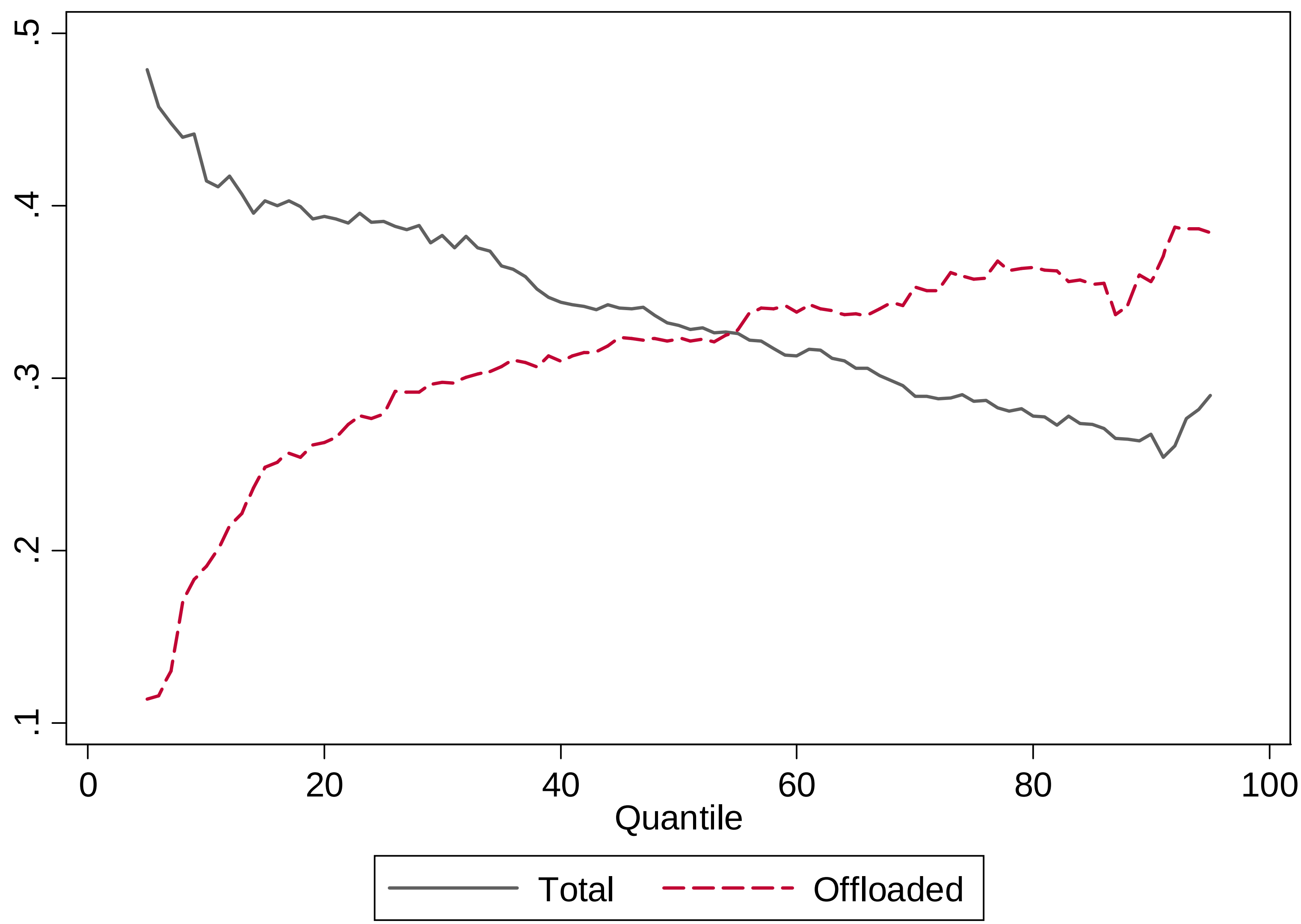

Figure 4: Average q-Sensitivities by Quantile. This figure plots the weighted average q-sensitivity across the ten Credit Suisse/Tremont hedge fund strategies for all q between 5 and 95. The solid line plots average sensitivities from total returns, while the dashed line plots sensitivities from the 5%-quantile offloaded returns. The weighted averages are calculated using the weights displayed in the last column of Table 1.

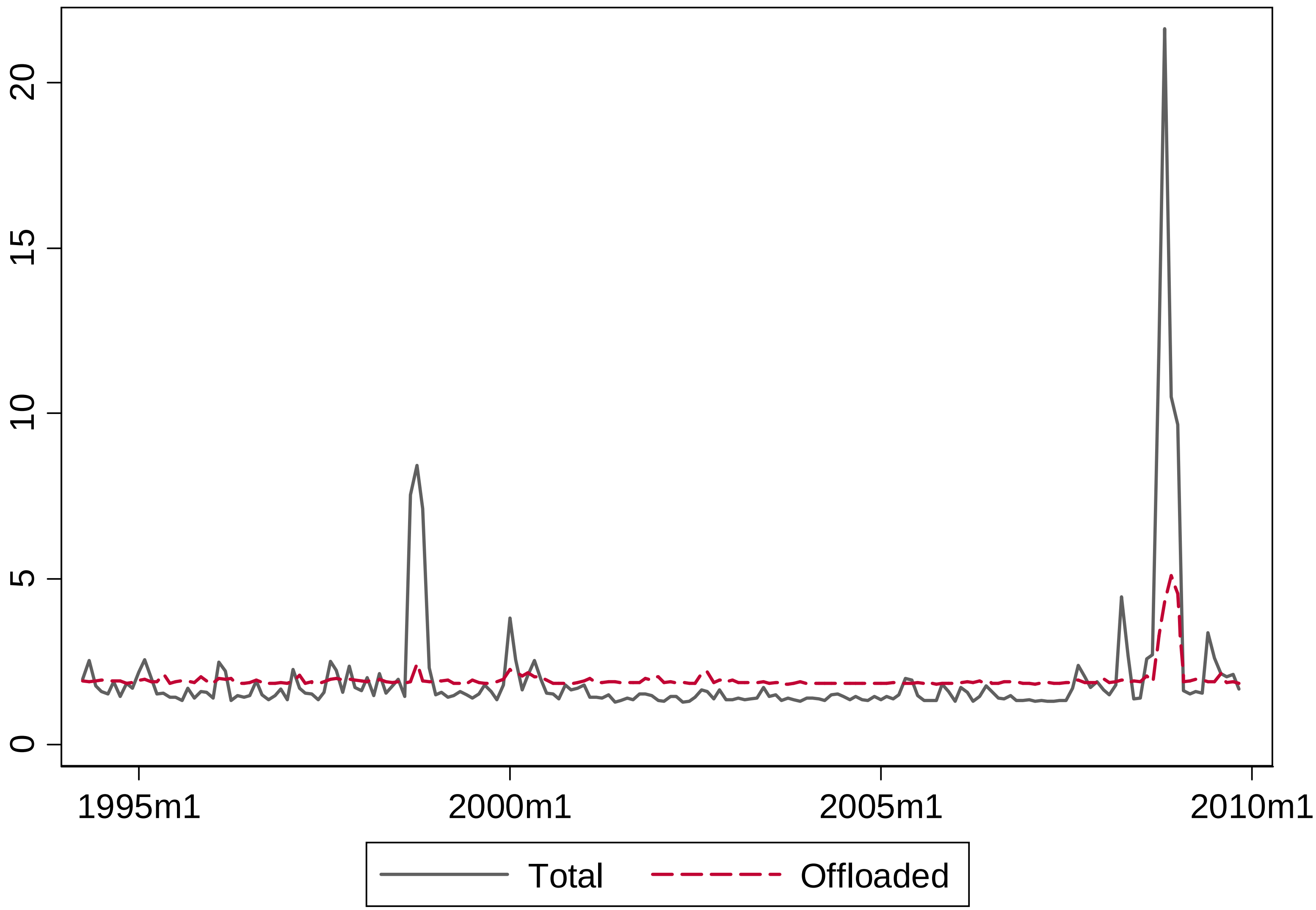

Figure 5: Average ARCH Covariances Over Time. This figure plots the average covariance across the ten hedge fund strategies, estimated using a multivariate BEKK-ARCH(2) model. The solid line plots the average covariance across total returns, while the dashed line plots the average across the 5%-quantile offloaded returns.

Table 1: Summary Statistics of Monthly Excess Returns. This table reports summary statistics for the ten Credit Suisse/Tremont hedge fund style returns. All returns are in excess of the 3-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-value 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, averaged over the sample period of January 1994 through November 2009. We also report the return to the overall hedge fund index. The market return is the cum dividend value-weighted CRSP return.

								Tests for Normality		Average
	Sharpe	Mean	Std Dev	Skew	Kurt	Min	Obs	Pr(Skew)	Pr(Kurt)	Weight
Hedge Fund Strategies										
Long/Short Equity	0.19	0.56	2.89	-0.06	6.44	-11.85	191	74%	0%	29%
Global Macro	0.25	0.73	2.96	-0.11	6.15	-11.89	191	51%	0%	25%
Event Driven	0.30	0.52	1.74	-2.61	17.78	-12.19	191	0%	0%	19%
Fixed Income Arbitrage	0.06	0.11	1.75	-4.00	28.69	-14.10	191	0%	0%	6%
Multi-Strategy	0.23	0.36	1.58	-1.69	8.71	-7.45	191	0%	0%	5%
Emerging Markets	0.10	0.44	4.51	-0.79	7.61	-23.45	191	0%	0%	5%
Equity Market Neutral	0.07	0.22	3.11	-11.87	155.83	-40.47	191	0%	0%	4%
Managed Futures	0.09	0.29	3.40	0.03	3.09	-9.80	191	86%	61%	4%
Convertible Arbitrage	0.16	0.33	2.07	-2.56	17.81	-12.65	191	0%	0%	4%
Dedicated Short Bias	-0.08	-0.37	4.88	0.73	4.54	-9.58	191	0%	0%	1%
Weighted Average	**0.20**	**0.51**								
Hedge Fund Index	0.21	0.47	2.24	-0.27	5.26	-7.97	191	12%	0%	
Market	0.09	0.44	4.65	-0.86	4.43	-18.55	192	0%	0%	

Table 2: Average q-Sensitivities - Monthly Excess Returns. This table reports the average of the bivariate 50%- and 5%- sensitivities for each of the ten Credit Suisse/Tremont hedge fund styles calculated using monthly excess returns. In addition, we calculate the percent change of the 5%-sensitivity relative to the 50%. The p-values test the null hypothesis that the percent change is zero, and are generated via bootstrap with 1000 draws.

	50%-sensitivity	5%-sensitivity	Percent change	p-value
Long/Short Equity	0.49	0.51	6%	0.830
Global Macro	0.29	0.44	52%	0.275
Event Driven	0.29	0.48	68%	0.045
Fixed Income Arbitrage	0.17	0.44	166%	0.018
Multi-Strategy	0.23	0.50	116%	0.002
Emerging Markets	0.76	0.94	25%	0.473
Equity Market Neutral	0.13	0.20	63%	0.799
Managed Futures	0.06	0.11	94%	0.798
Convertible Arbitrage	0.25	0.70	177%	0.002
Dedicated Short Bias	-0.73	-0.09	-87%	0.000
Weighted Average	**0.33**	**0.48**	**45%**	**0.064**

Table 3: Summary Statistics of Risk Factors. This table reports summary statistics for excess returns of seven risk factors. The CRSP market excess return is in excess of the 3-month Treasury bill rate and is from the Center for Research in Security Prices. The VIX straddle return is computed from the Black-Scholes (1973) formula using the CBOE's VIX implied volatility index, the S&P 500 Index, and the 3-month Treasury bill. The variance swap return is the difference between realized S&P 500 variance from closing daily data and the VIX implied variance. The repo/Treasury spread is the difference between the 3-month general collateral Treasury repo rate (from ICAP) and the 3-month Treasury bill rate. The carry-trade excess return is calculated using the Deutsche Bank carry USD total return index. The 10-year/3-month Treasury return is the return to the 10-year constant maturity Treasury bond 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.

					Tests for Normality		
	Sharpe	Mean	Std Dev	Min	Pr(Skew)	Pr(Kurt)	Obs
CRSP Market Excess Return	0.09	0.44	4.65	-18.55	0%	0%	192
VIX Straddle Excess Return	-1.06	-0.54	0.51	-1.43	0%	0%	191
Variance Swap Return	-0.38	-0.30	0.79	-0.84	0%	0%	191
Repo - Treasury Rate	1.00	0.01	0.01	-0.05	12%	0%	192
Carry-trade Excess Return	0.18	0.45	2.54	-14.26	0%	0%	191
10 Year - 3 Month Treasury Return	0.11	0.25	2.37	-6.24	27%	0%	191
Moody's BAA - 10 Year Treasury Return	0.07	0.14	2.05	-14.08	0%	0%	191

Table 4: Summary Statistics of Monthly Offloaded Returns. This table reports summary statistics for monthly 5%-quantile offloaded returns, calculated as the residuals to the 5%-quantile regression of raw returns on our seven factors. The weighted average is computed using the weights displayed in the last column of Table 1. The Sharpe ratio is the ratio of mean excess returns to the standard deviation of excess returns. The tests for normality give the p-value of Royston's (1991) test that skewness/kurtosis are normal.

							Tests for Normality	
	Sharpe	Mean	Std Dev	Skew	Kurt	Min	Pr(Skew)	Pr(Kurt)
Hedge Fund Strategies								
Long/Short Equity	-0.14	-0.32	2.37	2.78	19.00	-4.92	0%	0%
Global Macro	0.20	0.83	4.13	2.20	13.43	-6.94	0%	0%
Event Driven	-0.15	-0.25	1.70	3.20	24.87	-3.78	0%	0%
Fixed Income Arbitrage	0.04	0.05	1.31	0.13	2.94	-3.59	46%	96%
Multi-Strategy	0.13	0.19	1.42	-0.23	3.51	-4.55	20%	14%
Emerging Markets	0.19	0.74	3.92	0.09	3.77	-11.34	59%	5%
Equity Market Neutral	-0.16	-0.49	3.08	-9.60	120.40	-38.31	0%	0%
Managed Futures	-0.25	-0.99	3.95	0.66	3.90	-10.48	0%	3%
Convertible Arbitrage	0.40	0.62	1.56	0.34	3.47	-3.12	5%	16%
Dedicated Short Bias	0.01	0.02	3.01	0.42	3.06	-6.41	2%	67%
Weighted Average	**0.00**	**0.08**						
Difference Relative to Total Returns	**-0.20****	**-0.43****						

Table 5: CAPM Alphas of Monthly Total and Offloaded Returns. This table reports the CAPM alphas of our monthly total and offloaded returns for each of the ten hedge fund styles. The weighted average is calculated using the weights displayed in the last column of Table 1, and significance is obtained via bootstrap with 1000 draws.

	Total	Offloaded
Long/Short Equity	0.36**	-0.28
Global Macro	0.66***	0.91***
Event Driven	0.42***	-0.19
Fixed Income Arbitrage	0.04	0.02
Multi-Strategy	0.31***	0.17
Emerging Markets	0.20	0.76***
Equity Market Neutral	0.14	-0.45
Managed Futures	0.34	-0.92***
Convertible Arbitrage	0.26*	0.65***
Dedicated Short Bias	-0.01	0.10
Weighted Average	**0.40*****	**0.13**

Table 6: Average 5%-Sensitivities for Total and Offloaded Returns. This table reports average bivariate 5%-sensitivities calculated using monthly total and offloaded returns. We also calculate the percent change of the sensitivities using the offloaded returns relative to those using total returns. The p-values test the null hypothesis that the percent change is zero, and are generated via bootstrap with 1000 draws. The weighted average is calculated using the weights displayed in the last column of Table 1.

	Total	Offloaded	Percent change	p-value
Long/Short Equity	0.51	0.05	-90%	0.000
Global Macro	0.44	0.16	-63%	0.015
Event Driven	0.48	0.17	-65%	0.000
Fixed Income Arbitrage	0.44	0.04	-91%	0.000
Multi-Strategy	0.50	0.13	-73%	0.000
Emerging Markets	0.94	0.20	-79%	0.000
Equity Market Neutral	0.20	0.09	-58%	0.415
Managed Futures	0.11	0.09	-17%	0.932
Convertible Arbitrage	0.70	0.08	-89%	0.000
Dedicated Short Bias	-0.09%	-0.02%	-79%	0.386
Weighted Average	**0.48**	**0.11**	**-76%**	**0.000**

Table 7: Flow-Performance Regressions. This table reports the results of panel regressions run with time and strategy fixed effects. The left hand side variables are monthly flows into strategies relative to total flows into the hedge fund sector. The right hand side variables are (i) past monthly returns, (ii) past annual returns, (iii) the annual rolling alpha, (iv) the annual rolling Sharpe ratio, (v) the annual rolling standard deviation, and (vi) the expanding window seven-factor VaR computed as the predicted value from a 5%-quantile regression on the seven pricing factors with a minimum of 24 months of data (i.e., in-sample for the first 24 months).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
LAGGED VARIABLES										
Monthly Return	0.04***	0.03***	0.04***	0.05***	0.04***	0.03***	0.04***	0.04***	0.04***	0.04***
Annual Return	0.01***	0.01***	0.01***			0.01***	0.01***		0.00***	0.01***
Alpha	0.01*							0.01*	0.01*	0.01*
Sharpe Ratio	0.01				0.06**	-0.01	0.01			
Standard Deviation	0.01	0.01	0.01				0.01			0.01
VaR	0.01***		0.01**	0.01**			0.01**			0.01***
Constant	-3.80***	-0.21	-3.95***	0.68	-2.92***	-3.13***	-3.94***	-2.84***	0.23	-3.80***
Observations	1680	1800	1680	1680	1800	1800	1680	1800	1800	1680
Adjusted-R^2	10.2%	9.6%	10.1%	9.0%	9.0%	9.6%	10.1%	8.9%	9.7%	10.3%