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Downside Risk in Hedge Funds and Commodity Trading Advisors (CTAs):Whose Tails Are Hidden?

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Abstract

This paper examines the underestimation problem of downside risk in hedge funds, commodity trading advisors (CTAs), and funds of hedge funds (FOFs). Using value at risk (VaR) and expected shortfall (ES) as downside risk measures, I find that CTAs on average have a higher downside risk than hedge funds and FOFs, but hedge funds and FOFs have a more severe underestimation problem of downside risk than CTAs. During 1994-2008, the cross-sectional average of CTAs' average loss during 5% tail events measured by ES is 10.18% per month while the corresponding values for hedge funds and FOFs are 8.07% and 5.60%, respectively. When back-tested by the frequency of actual loss breaching estimated VaR, hedge funds and FOFs on average failed the proportion of failure (PF) test but CTAs did not. Among hedge funds, the degree of underestimation varies significantly across investment styles, and emerging market funds and short sellers have the most severe underestimation problem.

JEL classification: G11, G12, G23, G32

Key words: downside risk, VaR, hedge funds, commodity trading advisors

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1. Introduction

Risk-management weakness at financial institutions is one of the most significant factors contributing to the financial turmoil in 2007-2008 (PWG (2008)). To prevent similar crises recurring, it is important to examine if there is any fundamental problem in the risk management practice that may cause errors when measuring risk. The portfolio theory pioneered by the seminal work of Markowitz (1952) is based on the assumption that returns on assets are normally distributed. Under the assumption, total risk can be measured by volatility, and tail events deviating more than three standard deviations from the mean are very rare. However, financial market history shows that the assumption is violated. For example, if return on S&P500 index has a normal distribution, a daily return lower than -3.72% should not be observed more than once in 90 years, but such tail events occurred thirteen times during 1950 – 2009.[1]

The issue of tail risk is most problematic in alternative investments because hedge funds have trading strategies and fee structures that cause negatively-skewed payoffs and fat tails (Mitchell and Pulvino (2001), Goetzmann, Ingersoll and Ross (2003), and Agarwal and Naik (2004)). After the near collapse of Long Term Capital Management (LTCM) in 1998, hedge fund researchers realized the limitation of volatility and analyzed downside risk in hedge funds. For example, Agarwal and Naik (2004) find that the mean-variance analysis substantially underestimates tail losses and this underestimation is most severe in portfolios of hedge funds with low volatility. Liang and Park (2007 and 2010) show that VaR and ES are better risk measures than volatility in terms of predicting hedge fund failure and explaining the cross-sectional variation in hedge fund returns.

The problem in measuring and managing downside risk is the fact that tail events, by definition, are observed rarely and therefore historical return data may not contain such events. This problem exists in traditional assets such as stocks, bonds, and mutual funds as well, but it becomes more problematic in hedge funds, CTAs, and FOFs that usually report returns no more frequent than monthly.[2] Therefore, downside risk in alternative investments is easily underestimated when we depend solely on historical data.

Young funds have the most severe problem of underestimated risk, but investors cannot simply avoid young funds because these funds may have skills that have not been diluted by high

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[1] This argument is based on the fact that daily return on S&P500 index has a mean of 0.0325% and a standard deviation of 0.9651% during 1950 – 2009. As -3.72% deviates 3.89 standard deviations from the mean, returns higher than -3.72% have a probability of 0.99995 if the return distribution is normal.

[2] CTAs receive compensation from investors for providing advice on options and futures, and the actual trading of managed futures accounts, and they are required to register with the Commodity Futures Trading Commission (CFTC).

capital inflows yet. Aggarwal and Jorion (2010) find outperformance of emerging hedge fund managers during the first two to three years of existence, and this finding is after adjusting for backfill and other biases. Boyson (2008) finds that persistence of hedge fund performance is strongest among young funds.

This paper compares hedge funds with CTAs and FOFs in terms of downside risk in order to shed light on which alternative investment strategy has the most severe underestimation problem of downside risk. Using Lipper TASS hedge fund data (hereafter, TASS) for the period of 1994-2008, I find that CTAs on average have a higher downside risk than hedge funds, but the tails of hedge funds are more likely to be hidden than the tails of CTAs. I use this finding to explain why CTAs have grown rapidly in recent years. Previous research shows CTAs have a poor performance under the mean-variance framework and argues that CTAs persist despite poor performance due to information asymmetry (Elton *et al.* (1987 and 1990) and Bhardwaj *et al.* (2008)). However, I show that downside risk should be considered when analyzing the risk-return trade-off of CTAs and other alternative investments, and the rapid growth of CTAs is related more to downside protection and diversification benefit than to information asymmetry.

The rest of this paper is organized as follows. Section 2 describes the data and explains how to estimate downside risk. Section 3 compares hedge funds with FOFs to examine whether downside risk is reduced by diversification. Section 4 presents the PF test to examine the severity of the underestimation problem of downside risk in hedge funds, FOFs, and CTAs. Section 5 examines the growth of CTAs and discusses the benefit of downside protection provided by CTAs. Section 6 concludes the paper.

2. Data and Risk Measures

2.1. Data

Net-of-fee monthly returns, assets under management (AUM), and other characteristics of hedge funds, CTAs, and FOFs are obtained from TASS. TASS is the most widely utilized hedge fund database in the literature. The fund characteristics provided by TASS includes investment styles, fee structure, high-water marks, minimum investment, subscription and redemption information, lockup provisions, and so on[3].

[3] See "Dow Jones Credit Suisse Hedge Fund Indexes" website for detailed information on investment styles: http://www.hedgeindex.com/hedgeindex/en/indexoverview.aspx?indexname=HEDG&cy=USD

To reduce survivorship bias, I include both live and defunct funds in our analysis.[4] TASS includes information on defunct funds as well as live funds, but the graveyard database does not retain funds dropped out of the live fund database before 1994. Thus the estimation period starts in January 1994 and ends in December 2008 (180 months).

As of December 2008, there are 8086 funds in TASS. This number is obtained after I exclude those funds that report i) returns not in US dollars, ii) quarterly (not monthly) returns, or iii) gross return (not net-of-fee returns) from the original TASS database. There is another requirement for a fund to be included in the analysis. Funds with less than 24 months of return history are not included because I require a fund has at least 24 months return history to estimate downside risk. After imposing the two-year return history requirements, there are 6627 funds (4640 hedge funds, 524 CTAs, and 1464 FOFs) in the database. Table 1 shows the summary statistics of these funds.

As shown in the table, returns on hedge funds and FOFs are left-skewed and leptokurtic on average. A normal distribution should have a skewness of zero and a kurtosis of three, but seven out of nine hedge fund strategies show negative skewness (average -0.37) and all the nine strategies have a kurtosis higher than three (average 7.78). For a formal test of the normality assumption widely utilized in finance theories, I use Jarque-Bera (1980) test and find that 60.52% of hedge funds, 43.98% of CTAs, and 64% of FOFs reject the normality assumption at the significance level of 1 percent during 1994-2008. This finding is consistent with Bali *et al.* (2007) and Cremers *et al.* (2005), and it confirms that we need downside risk measures for alternative investments because volatility cannot reveal the true risk when returns show non-normality.

Table 1

Statistical summary of return and risk, and the test for normality

This table shows the cross-sectional average values of the average, standard deviation, skewness, kurtosis, VaR_95, and ES_95 of monthly returns of funds in each investment style. It also shows the percentage of funds in each style that fail the Jarque-Bera (JB) test for normality at the significance level of 1 percent[5]. The data is from TASS database, and the sample period is from

[4] For the details on biases in hedge fund databases, see Fung and Hsieh (2000 and 2002). For the reasons why funds drop out of the live fund database and move to the graveyard, see Liang and Park (2010).

[5] $JB = n\left[S^2/6 + (K-3)^2/24\right]$, where *S* is skewness, *K* is kurtosis, and *n* is number of observations. This is a joint test of *S* = 0 and *K* = 3. The JB statistic has a Chi-square distribution with two degrees of freedom.

January 1994 to December 2008. To be included in the analysis, each fund should have at least twenty four monthly return data during the sample period.

Investment Style	Number of Funds	Average Return (%)	Standard Deviation (%)	Skewness	Kurtosis	VaR_95 (%)	ES_95 (%)	% Rejection in
Convertible Arbitrage	195	0.47	2.41	-1.01	10.69	2.98	5.51	64.62
Dedicated Short Bias	41	0.30	5.71	0.31	4.71	7.66	10.75	43.90
Emerging Markets	390	0.72	6.23	-0.83	8.84	8.50	13.57	69.23
Equity Market Neutral	352	0.55	2.56	-0.30	8.26	2.89	4.86	53.13
Event Driven	570	0.81	2.88	-0.46	7.98	3.26	5.51	72.11
Fixed Income Arbitrage	290	0.51	2.37	-1.48	15.13	2.61	5.54	77.24
Global Macro	323	0.59	4.16	0.09	5.94	5.54	7.78	50.77
Long/Short Equity Hedge	2001	0.88	5.29	-0.07	6.29	6.30	9.30	55.27
Multi-Strategy	478	0.61	3.10	-0.64	8.44	3.92	6.35	63.18
Hedge Funds	*4640*	*0.74*	*4.26*	*-0.37*	*7.78*	*5.20*	*8.07*	*60.52*

CTAs	*523*	*0.86*	*5.91*	*0.19*	*5.45*	*7.41*	*10.18*	*43.98*
Fund of Funds	*1464*	*0.41*	*2.55*	*-0.89*	*7.88*	*3.51*	*5.60*	*64.00*
All Funds	*6627*	*0.68*	*4.01*	*-0.44*	*7.62*	*5.00*	*7.69*	*59.98*

2.2. Downside Risk Measures: VaR and Expected Shortfall

I use 95% Value at Risk (VaR_95) and 95% Expected Shortfall (ES-95) estimated by non-parametric methods as measures of downside risk. I define the 5th percentile of the empirical distribution of a fund as VaR_95 of a fund, and ES_95 is the conditional average of the returns lower than VaR_95.

Formal definitions are as follows. Let $R_{t+\tau}$ denote the return on a fund during the period between t and $t+\tau$. Let $F_{R,t}$ denote the cumulative distribution function (CDF) of $R_{t+\tau}$ conditional on the information available at time *t*. $F_{R,t}^{-1}$ denotes the inverse function of $F_{R,t}$. The VaR of the fund as of time *t* with a time horizon τ and a confidence level $1-\alpha$ is:

$$VaR_t(\alpha,\tau) = -F_{R,t}^{-1}(\alpha) \tag{1}$$

This paper uses a 95% confidence level ($\alpha = 0.05$) and a time horizon (τ) of 1 month, which is the frequency of TASS return data. As I use a nonparametric approach to estimate VaR and do not impose any parametric assumption on the distribution of a fund's return, this method is based solely on the left tail of the actual empirical distribution.

In addition to VaR, I use ES as a downside risk measure because ES has some desirable properties that VaR does not have.[6] Artzner *et al*. (1999) show that ES is a coherent risk measure as it has sub-additivity and continuity, but VaR does not have such desirable properties. Another

[6] ES is sometimes called conditional VaR, tail conditional expectation, conditional loss, or tail loss in the literature.

advantage of ES is, VaR does not provide information on how big the loss could be once it is breached, but ES measures this quantity. ES is the average loss greater or equal to VaR and the formal definition is as follows:

$$ES_t(\alpha,\tau) = -E_t[R_{t+\tau} \,|\, R_{t+\tau} \le -VaR_t(\alpha,\tau)] = -\frac{\int_{v=-\infty}^{-VaR_t(\alpha,t)} v f_{R,t}(v)dv}{F_{R,t}[-VaR_t(\alpha,\tau)]} = -\frac{\int_{v=-\infty}^{-VaR_t(\alpha,t)} v f_{R,t}(v)dv}{\alpha} \qquad (2)$$

where $R_{t+\tau}$ denotes the fund return during the period between t and $t+\tau$, $f_{R,t}$ denotes the conditional probability density function (PDF) of $R_{t+\tau}$, and $F_{R,t}$ denotes the conditional cumulative distribution function (CDF) of $R_{t+\tau}$ conditional on the information available at time *t*. $F_{R,t}^{-1}$ denotes the inverse function of $F_{R,t}$ and $1-\alpha$ is the confidence level.

3. Can Downside Risk Be Reduced by Diversification?

It is well known that diversification reduces volatility, but there is little, if any, empirical evidence on whether downside risk can be mitigated by diversification. To my knowledge, this is the first paper that investigates this issue directly by comparing downside risk of individual hedge funds (not indexes) with that of FOFs which are portfolios of hedge funds. Previous research examines this issue using indirect approaches such as analyzing correlation or clustering of losses during down markets.

Using HFR index and logit models, Boyson *et al.* (2010) find that 10% tails of hedge fund style indexes cluster, which implies that diversification benefit may be reduced when investors really need it. Using Credit Suisse/Tremont index data and quantile regression, Adrian and Brunnermeier (2007 and 2009) find that VaR of a hedge fund style index increases when other hedge fund style indexes have a high VaR. Edwards and Caglayan (2001) examine the performance of hedge funds and CTAs in bear versus bull stock markets and find that CTAs do not produce as high returns in bull markets as hedge funds, but they provide better diversification against a declining stock market than hedge funds.

While previous research provides some evidence on the difficulty of reducing downside risk by diversification, it is not clear to what extent the limit of diversification is. This paper directly measures the effect of diversification by comparing VaR and ES of hedge funds with those of FOFs. As shown in Table 1, on average, FOFs have a lower VaR_95 (monthly tail loss of 3.51% vs. 5.20%) and a lower ES_95 (monthly conditional average loss of 5.60% vs. 8.07%) than hedge funds, which means downside risk can be reduced by diversification. On average CTAs have a higher VaR_95 (7.41%) and a higher ES_95 (10.18%) than hedge funds, but some hedge fund styles (emerging market funds, for example) have higher VaR and ES than CTAs. Note that there is a large variability in downside risk across different hedge fund investment styles.

I also use the time series of ES_95 estimated in the rolling five-year estimation windows to compare downside risk in hedge funds and FOFs. Note that ES_95 in Table 1 is like a snapshot because the entire return history of each fund during 1994-2008 is used to estimate ES, while Figure 1 is like a video showing the time variation because ES_95 in Figure 1 is based on rolling five-year estimation period. For example, ES_95 of a hedge fund as of January 1999 is estimated using all the available (must be 24 or more) return observations of the fund during the period between January 1994 and December 1998. For each time period, I estimate ES_95 of each fund, take the cross-sectional average, and plot the average on Figure 1.

Figure 1. Underestimated Downside Risk in Hedge Funds and FOFs

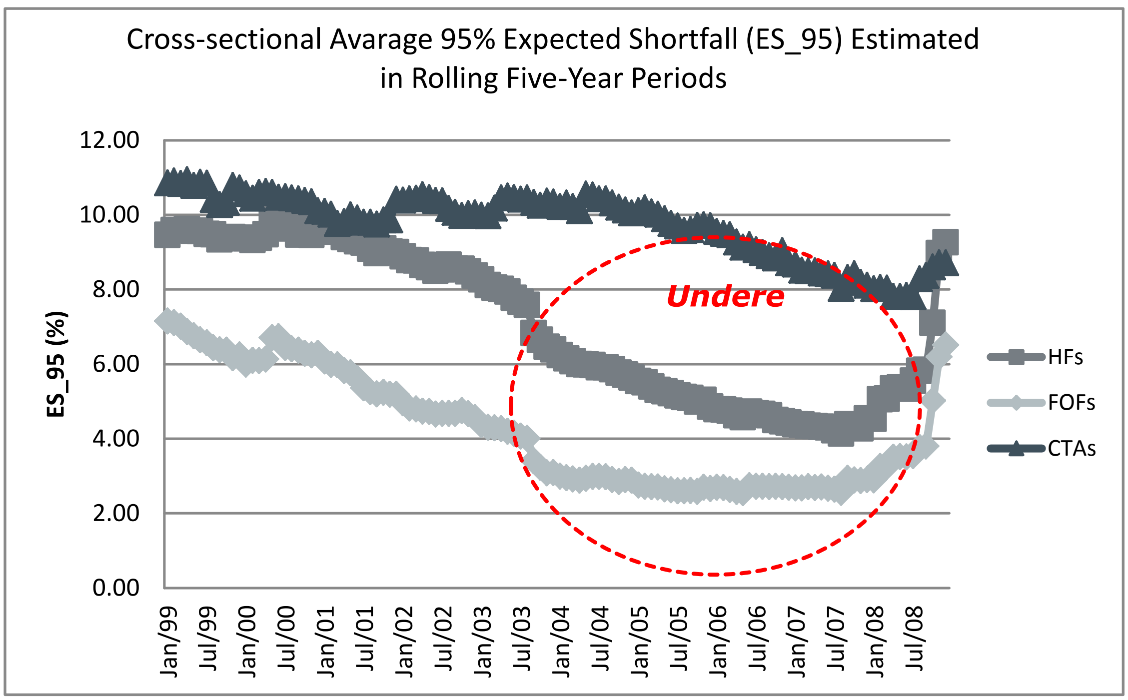


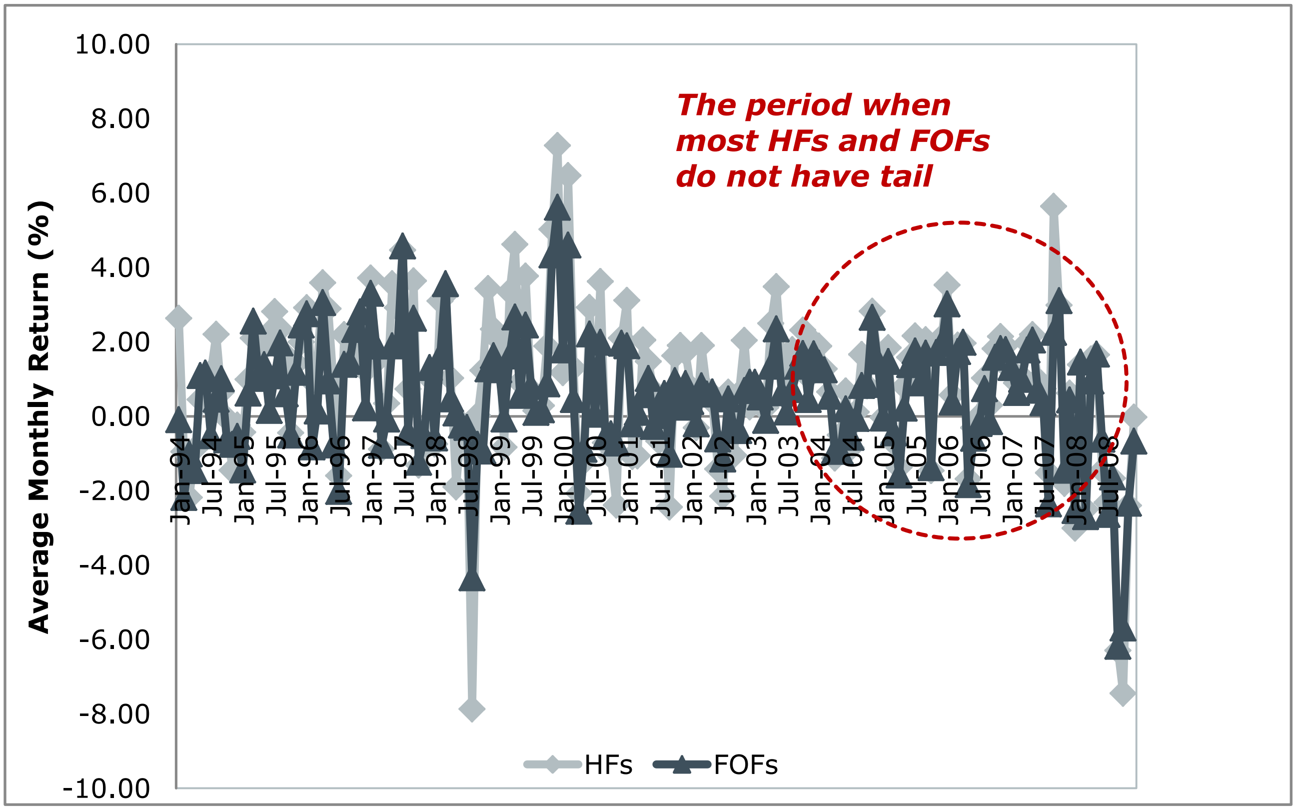
Figure 1 shows that downside risk can be reduced by diversification. Note that in all the time periods FOFs on average have a lower downside risk than hedge funds and CTAs due to diversification. CTAs have higher downside risk than hedge funds most of the time. In addition to diversification, another important fact revealed by this figure is the underestimation problem of downside risk in hedge funds and FOFs during the period right before the financial crisis of 2008, and this is the topic that I analyze in the next section.

4. Underestimation problem of Downside Risk in Hedge Funds, FOFs, and CTAs

The basic framework of measuring risk and return on an asset in finance is to use the historical return data on the asset. However, tail events are often not included in the return history because they are, by definition, rarely observed. Therefore, downside risk can be easily underestimated, and Figure 1 illustrates this problem. The time period in the figure starts in Jan 1999 as the data used in this analysis starts in Jan 1994 and rolling previous five years are used to estimate ES_95. Note that the first five year period, Jan 1994 - Dec 1998, includes tail events such as Asian Financial Crisis in 1997 and the LTCM failure in 1998. This is why the levels of ES_95 start high (averages of CTAs: 10.85%, hedge funds: 9.46%, and FOFs: 7.15%) in Jan 1999.

As time proceeds, average ES_95 of HFs and FOFs shows a decreasing pattern because more and more new funds that do not have tail events in their return history enter the database. Note that there is a sudden drop in average ES_95 of FOFs and HFs in September 2003 when the big tail event, LTCM in 1998, drops out of the rolling five-year estimation window. ES_95 of hedge funds and FOFs continue to decrease to show a minimum at August 2007 because most funds do not have tail events in the five-year estimation windows as illustrated in Figure 2. The cross-sectional average ES_95 of hedge funds is between 9.89% and 4.14% depending on whether tail events could be observed or not, and I call this the underestimation problem of downside risk in hedge funds. Similarly, the cross-sectional average ES_95 of FOFs varies between 7.15% and 2.55%. That is, downside of hedge funds and FOFs may be underestimated by about 60%, but we do not observe this type of underestimation problem in CTAs.

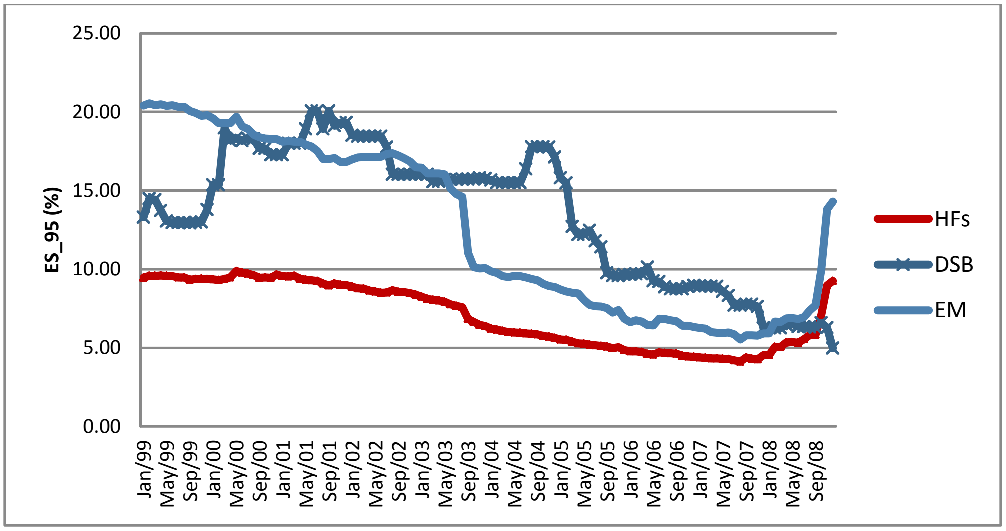
Figure 2. Time Series of Cross-sectional Average Returns on Hedge Funds and FOFs



Note that 60% underestimation is just the average for all hedge funds and there is a very wide variability in the severity of this underestimation problem across different hedge fund investment styles. For example, Figure 3 illustrates that emerging market funds (EM) and dedicated short bias funds (DSB) have much severe underestimation problem than an average hedge fund.[7] The cross-sectional average ES_95 of emerging market funds is between 20.55% and 5.54% depending on whether tail events are in the return history or not, and the corresponding range of dedicated short bias funds is between 20.06% and 4.98%. That means downside risk of emerging market funds and short sellers may be underestimated by more than 70%. Figure 3 also shows that short sellers' tail risk is the highest during the bull markets and their tail is hidden during financial crises when other funds' tails are uncovered.

[7] To save space, I do not include detailed information on the underestimation problem of other hedge fund investment styles, but the information is available from the author upon request.

Figure 3. Downside Risk in Emerging Market Funds (EM) and Short Sellers (DSB)



Using simple illustrations, this section opened the discussion of the underestimation problem of downside risk in hedge funds and FOFs. Now I provide more formal analyses of this problem using the proportion of failure (PF) test. As the VaR_95 of a fund predicts that the loss on the fund would not exceed VaR_95 at the confidence level of 5 percent, the loss would exceed VaR_95 more than 5 percent of the time if downside risk is underestimated. Kupiec (1995)'s PF test is the test statistic based on this simple idea and it is most widely utilized in VaR back testing. PF is defined as follows.

$$PF = 2\ln\left(\left(\frac{1-\hat{\alpha}}{1-\alpha}\right)^{T-N}\left(\frac{\hat{\alpha}}{\alpha}\right)^{N}\right) \tag{3}$$

Where T is the number of trials, N is the number of exceptions (the number of months when actual loss exceeds estimated VaR), α is the significance level of VaR (0.05 for VaR_95), and $\hat{\alpha}$ is N/T, the observed frequency of exception. Under the null hypothesis (H_0) of $\alpha = \hat{\alpha}$, PF is asymptotically distributed as chi-squared with one degree of freedom.

At each month during the ten year period between Jan 1999 and Dec 2008, I compared the realized return of each fund with the VaR_95 based on the previous 60 months rolling estimation window to find the PF of each fund. Table 2 shows the cross-sectional average of PF for each investment style and the proportion of funds that reject the null hypothesis at the significance level of 1 percent and 5 percent.

Table 2

Proportion of Failures: A Statistical Test of 95% VaR in 1999 – 2008

This table presents Kupiec (1995)'s *proportion of failures* (PF) test of VaR during the period between 1999 and 2008. PF is asymptotically distributed a chi-squared with one degree of freedom, and the reported PF statistics are cross-sectional averages in each investment style. The proportions of funds that reject the null hypothesis (5% rejection for 95% VaR) at the 1% and the 5% level are also reported. Rolling five-year estimation window and a nonparametric method is used to estimate 95% VaR (VaR_95), and the estimated VaR is compared with the realized return to determine failure. To be included in the analysis, a fund should have at least twenty-four months when its VaR can be tested. *, **, and *** denote statistical significance at the 1%, 5%, and 10% level, respectively.

Investment Style	1999 – 2008 (10 years)				1999 – 2003 (5 years)				2004 – 2008 (5 years)				PF'04-'08 – PF'99-'03
	Number of	PF	% Rejectio		Number of	PF	% Rejectio		Number of	PF	% Rejectio		
			1	5			1	5			1	5	
Convertible Arbitrage	140	6.15**	33.6	52.9	74	3.91**	10.8	24.3	101	5.64**	28.7	47.5	1.40
Dedicated Short Bias	26	1.57	0	7.7	20	1.52	0	15.0	17	0.96	0	5.9	-1.01
Emerging Markets	229	3.85**	20.1	34.9	138	0.68	0	2.2	185	5.59**	30.3	57.3	12.64***
Equity Market	202	4.18	23.	34.	91	4.85	17.	27.	162	3.47*	19.	29.	-1.00

Neutral		**	3	6		**	6	5			1	0	
Event Driven	387	6.15**	35.7	48.3	194	2.68	12.4	21.1	315	6.54**	37.5	55.2	7.52***
Fixed Income Arbitrage	164	6.04**	31.7	44.5	68	4.03**	16.2	26.5	139	5.94**	32.4	48.9	1.47
Global Macro	159	2.88*	13.2	20.1	69	1.82	4.4	13.0	129	2.94*	15.5	23.3	1.70*
Long/Short Equity Hedge	1258	3.58*	19.0	31.9	621	1.98	8.4	17.6	990	3.87**	19.7	35.4	9.40***
Multi-Strategy	271	5.24**	33.5	47.9	108	1.96	8.3	11.1	252	6.10**	37.7	56.6	7.49***
Hedge Funds	2836	4.36**	23.9	36.9	1383	2.33	8.9	17.2	2290	4.72**	25.6	42.1	12.62***
CTAs	270	1.67	22.9	31.5	173	1.59	5.2	16.2	204	1.53	4.9	9.8	-0.21
Fund of Funds	995	6.07**	37.9	55.8	409	1.40	4.6	9.5	882	7.55***	49.8	70.3	25.81***
All Funds	4101	4.60**	26.1	39.8	1965	2.07	7.7	15.5	3376	5.27**	30.7	47.5	21.61***

Table 2 shows that hedge funds and FOFs on average fail PF test but CTAs do not during the ten year period between 1998 and 2008.[8] Six out of the nine hedge fund styles fail the PF test

[8] Note that hidden tail problems prevail in hedge funds but not in CTAs because CTAs perform well during extreme down markets such as the near collapse of LTCM in August 1998 and the bankruptcy of Lehman Brothers in September 2008.

at the 5 percent significance level and two styles fail the test at the 10 percent significance level. Dedicated short bias is the only investment style that does not reject the null hypothesis, but we should note that short sellers' tail is uncovered during bull markets and their tail is hidden during financial crises. As extreme bull markets (tail events for short sellers) are not in the return history of the short sellers during the testing period, PF test cannot reveal the hidden tails of short sellers. This also shows the limit of using historical return data to estimate risk in financial assets.

Table 2 also shows the sub-period analysis results for the five year periods 1999-2003 and 2004 – 2008, and the difference in average PFs of these two sub-periods. During the 1993-2003 period when most funds do not have tail events in their return history, neither hedge funds nor FOFs do not reject the PF test on average, and less than 9% of hedge funds and less than 5% of FOFs reject the test at the significance level of 1 percent. This means tail risk remains hidden for most of funds during this sub-period. However, during the sub-period of 2004-2008, most hedge fund styles and FOFs reject the PF test on average revealing their hidden tails. The most significant difference between these two sub-periods is observed in FOFs and in emerging market funds.

Table 3

Underestimated Downside Risk for Funds without Tail Event in the Return History

This table presents the differences in the out-of-sample average return and in the estimated ES_95 between the funds that have a tail event in the return history and the funds without a tail event. As of the last month when the five-year estimation period includes the LTCM tail event, I divide funds into two groups, funds with the tail event and funds without the tail event in their return history. I compare the expected return and estimated ES_95 of these two groups to quantify the degree of underestimation problem. As expected returns are not directly observable, I use the average return for the next sixty-month period as the proxy for the expected return, and estimated ES is based on the previous five-year estimation window. ***, ** and * denote the difference is significant at the 1%, 5%, and 10 level, respectively.

		Funds with Tail Events	Funds without Tail Events	Difference	*t*-statistic
Hedge Funds	Number	829	806		
	Expected Return	1.15	1.11	0.04	0.94

	Estimated Risk (ES_95)	9.5	5.6	3.90	12.29***
CTAs	Number	106	50		
	Expected Return	1.31	1.28	0.03	0.08
	Estimated Risk (ES_95)	10.78	9.75	1.03	0.95
FOFs	Number	268	256		
	Expected Return	0.77	0.72	0.05	1.16
	Estimated Risk (ES_95)	5.52	2.42	3.10	9.93***
All Funds	Number	1,203	1,112		
	Expected Return	1.08	1.03	0.05	1.08
	Estimated Risk (ES_95)	8.73	5.05	3.68	14.46***

Table 3 presents another test of the underestimation problem using ES. I divide funds into two groups; funds with tail events and funds without tail events in their return history, as of the last month when the five-year estimation period includes the near bankruptcy of LTCM in 1998. Table 3 shows that hedge funds and FOFs have the underestimation problem of downside risk but CTAs do not have the problem. Funds with tail events have the same expected return as the funds without tail events in their return history, but the estimated ES is different in hedge funds and FOFs. The difference is significant both statistically and economically.

Hedge funds with tail events have the average estimated ES of 9.5% and the corresponding value for hedge funds without tail events is 5.6%, and the difference is significant at the 1 percent level. FOFs also show similar underestimation problem. ES averages of FOFs with and without tail events are 5.52% and 2.42%. That is, the degree of underestimation in the downside risk of hedge funds and FOFs is 41 – 56%. This section shows that hedge funds and FOFs suffer a severe underestimation problem of downside risk while CTAs do not have the same problem. I use this finding to provide an alternative explanation on the performance and persistence of CTAs in the next section.

5. Rapid Growth of CTAs: Asymmetric Information or Downside Protection?

Elton *et al.* (1987) is the first comprehensive study of the risk and return of CTAs. Using standard deviation as a risk measure and Sharpe ratio as a performance measure, they argue that CTAs are neither an attractive alternative to bonds and stocks nor a profitable addition to a portfolio of stocks and bonds. At the time of publication, this article received significant attention from practitioners who suggested that CTAs might be desirable because of attractive skewness even though they have low mean return and high volatility.

In response to the comments received from the industry, Elton *et al.* (1990) analyze the skewness of CTAs and conclude that the degree of positive skewness of CTAs is too small to provide a good reason for investing in CTAs. They argue that CTAs are not attractive investments unless management fees and transaction costs are lowered. However, in contrary to their arguments, investors were more attracted to this industry and hence CTAs grew very rapidly over the next decades.

The total assets under management (AUM) of CTAs in the TASS database have increased from \$2.64 billion in Jan 1994 to \$45.42 billion in Dec 2008. The annual average growth rate is 20.87 percent during the period 1994 - 2008. Using longer return history (1980 – 1988 vs. 1994 – 2008) but the same risk and performance measures (standard deviation and Sharpe ratio), Bhardwaj *et al.* (2008) confirm the findings of Elton *et al.* (1987 and 1990), and argue that CTAs persist as an asset class despite poor performance because investors' experience of poor performance is not common knowledge due to the information asymmetry.

However, these researches consider neither downside risk in investments nor the underestimation problem of downside risk. CTAs may look unattractive under the traditional mean-variance framework, but they might be desirable under a new and more complete portfolio theory that considers downside risk. As explained in previous sections, standard deviation is no longer a valid measure of total risk in financial assets. CTAs have an advantage over other assets in terms of the underestimation problem of downside risk as shown in Table 2 and Table 3. This finding is consistent with Edwards and Caglayan (2001) who show that CTAs offer better downside protection than other assets even though their study and this paper use very different methodology and data[9].

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[9] Edwards and Caglayan (2001) analyze downside protection by dividing the returns of hedge funds and CTAs in Managed Accounts Reports (MAR) database into S&P500 index's down months and up months. This paper

6. Conclusion

This paper analyzes the underestimation problem of downside risk in hedge funds, CTAs, and FOFs. I find that CTAs have higher downside risk than hedge funds and FOFs, but the downside risk in hedge funds and FOFs are more likely to be underestimated than the downside risk in CTAs. Among hedge funds, the severity of the underestimation problem varies across the investment styles, and emerging market funds and short sellers have the most severe underestimation problem. That is, mean-variance analysis may not reveal the true benefit of adding CTAs to an investment portfolio. The rapid growth of CTAs in recent years may be attributable more to downside protection and diversification benefit than to information asymmetry.

One way to overcome the short history problem of young funds in the risk management of alternative investments is to use the return history of older funds that belong to the same investment style. That is, grouping funds based on their investment strategies, instruments, and area concentration is the first step, and using the history of old funds in the same category to estimate the consequences of tail events is the next step. I follow the style classification of TASS in this paper, but the finer the category, the better the outcome in uncovering hidden tails of young funds.

One caveat in using this approach to analyze downside risk is that this method works only for tail events that have already been experienced by old funds in the same investment category. For example, during the estimation period of this paper (1994 – 2008), we do not have a period of high inflation. That is, the return history of hedge funds, CTAs, and FOFs does not reveal how these funds would behave if interest rate risk becomes a major concern of investors. This is another source of hidden tail that is being underestimated when analyzing the risk profile of hedge funds using historical return data.

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measures downside risk of hedge funds and CTAs in TASS database using VaR and ES and analyzes the underestimation problem of VaR using the PF test.

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