Effect of booms or disasters on the Sharpe Ratio

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ABSTRACT

The purpose of this paper is to analyze the effect of either booms or disasters on the Sharpe Ratio. We provide a closed form expression of the Sharpe Ratio of an index whose log-return follows an arbitrary distribution. That is, besides variance, we allow for skewness, kurtosis and higher cumulants of the log-return to be non-zero. Our article has two main contributions. First, the Sharpe Ratio depends on all the cumulants and not just the mean and variance. Second, negatively skewed log-returns have a higher Sharpe Ratio than positively skewed returns. As a corollary, we explain why many hedge funds sell disaster insurance. Selling insurance by shorting options generates negative skewness, which in turn increases the Sharpe Ratio.
I. Introduction

In August 1998 — during the Russian financial crisis — the market dropped by 15.65%. During the same month, Event-Driven-Multi-Strategy (EDMS) hedge fund dropped by 6.73%. If returns are normally distributed, then the market drop takes place once every 641 years while the EDMS drop takes place once every 17,000 years. EDMS drop is rarer because of its lower volatility.\(^1\) Such a large and a seemingly unlikely drop turns out to be quite likely. In October 2008 — approximately ten years later — the market dropped 17.15% while the hedge fund dropped 7.33%. The size of the market’s drop takes place once every 2,400 years, while the size of EDMS’s drop takes place once every 95,000 years.

These events show one key feature of returns: extreme or fat-tailed events occur more often than predicted by the normal distribution. Mathematically, a normally distributed log-return has finite first two cumulants (related to moments) and zero higher order cumulants, while fat-tailed log-returns have non-zero higher cumulants. Colloquially, log-returns subject to disasters exhibit negative skewness (the third cumulant) while log-returns subject to booms exhibit positive skewness. Furthermore both disasters and booms lead to higher kurtosis (the fourth cumulant).

Figures 1 and 2 describe the rolling five-year skewness and kurtosis of three funds: the market (dark line), EDMS (dotted line) and the Distressed Securities (DS) fund (dashed line). Two observations are in order. First, both skewness and kurtosis of all three funds is non-zero. This fact is neither surprising nor unique to the two hedge funds. Due to the use of derivatives and dynamic strategies, hedge fund returns are fat-tailed (Aragon and Martin (2012), Mitchell and Pulvino (2001), Malkiel and Saha (2005), Bali et al. (2007), Fung et al. (2008)). While, the fat-tailed returns is intuitive, the level of negative skewness may not be as intuitive. Empirically, negative skewness implies that the log-return of hedge funds is subject to disasters. That is,\(^1\)

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\(^1\)The monthly market and hedge fund returns span from December, 1989 to August, 2012. The monthly market return data is from Kenneth French’s website. The hedge fund data is from https://www.isenberg.umass.edu/centers/center-for-international-securities-and-derivatives-markets/cisdm-indices (hedge fund return database assembled by University of Massachusetts at Amherst). The average sample monthly return of EDMS is 0.81%; the average is approximately the same as that of the market. On the other hand, the sample monthly volatility of EDMS is approximately one-third of the market — EDMS volatility is 1.51% while the market volatility is 4.51%.
Figure 1: This figure plots the rolling five year sample skewness from monthly returns of the market, EDMS and DS hedge fund.

Hedge funds sell disaster insurance (Jiang and Kelly (2012)). Second, skewness and kurtosis of the hedge funds co-move with that of the market. The tail exposure may not be diversifiable, which may explain the seemingly superior risk-adjusted returns hedge fund returns Brown et al. (2011).

Agarwal and Naik (2004) analyze the non-diversifiable risk by using option based strategies. They show that payoff of various equity-oriented strategies resemble those from writing an out of the money put option on the equity index. Most of the time, there will be no payouts and the hedge fund will reap relatively stable option premiums. However, on rare occasions — events when the equity index experiences a large loss — hedge funds experience an even larger loss. Due to the tail risk, this strategy is particularly attractive when performance is measured based on the Sharpe Ratio. Again, this fact is not surprising. Ackermann et al. (1999) report that the Sharpe Ratio of hedge funds is often higher than that of the market. Figure 3 plots the rolling five-year Sharpe Ratio of the market, EDMS and DS. For any five-year sample period, the Sharpe Ratio of both EDMS and DS strategies is higher than that of the market.

The purpose of this paper is to clarify how investment strategies exposed to tail risk affect the
Figure 2: This figure plots the rolling five-year sample kurtosis from monthly returns of the market, EDMS and DS hedge fund

Figure 3: This figure plots the rolling five-year “monthly” Sharpe Ratio of the market, EDMS and DS hedge fund
Sharpe Ratio. To do so, we analyze an index whose log-return follows an arbitrary distribution. The index may be a proxy for an investment strategy involving options. To achieve tractability, we use the cumulant generating function (CGF) of the log-return. The CGF captures all the information of the log-return. For example, if log-returns are normally distributed, only the first two cumulants of the log-return are non-zero. On the other hand, with an arbitrary distribution, all the cumulants can be non-zero. This construction allows us to calculate the Sharpe Ratio in closed form.

Our article two main contributions. First, the Sharpe Ratio depends on all the cumulants of the log-return. This result is subtle and can be confusing upon first glance. The Sharpe Ratio is a function of the first two moments of the Simple return. We show that the simple return is a non-linear function of the log-return. Therefore, it turns out that the volatility of the simple return depends on all the cumulants of the log-return. In this manner, Sharpe Ratio depends on all the cumulants of the log-return.

Second, we show how skewness, kurtosis or higher cumulants affect the Sharpe Raito. Specifically, we show that negative odd cumulants increase the Sharpe Ratio, while either positive odd cumulants or even cumulants decrease the Sharpe Ratio. In this manner, we explain the tail exposure of hedge fund strategies. Shorting options leads to log-returns subject to disasters — log-returns are negatively skewed. As a result, Sharpe Ratio is higher than that of the market. More importantly, we explain why hedge fund do not buy out of the money options. Going long options leads to positive skewness, which in turn leads to a lower Sharpe Ratio.


Even with the obvious drawbacks, Sharpe Ratio based performance measure remains the norm. Eling and Schuhmacher (2007) formally justify the norm using a decision theoretic analysis. However, inspite of the theoretical foundation, as explained before, Sharpe Ratio can be inflated (Goetzmann et al. (2002)). For example, using reasonable parameters, Goetzmann et al. (2002) show how shorting options can inflate the Sharpe Ratio. In this sense, our paper is a complement to Goetzmann et al. (2002). We give a precise reason for why shorting options leads to a higher Sharpe Ratio, while going long options leads to a low Sharpe Ratio.

To show our result explicitly, we analyze a numerical example. The example consists of four cases. The first case — the benchmark case — considers the Sharpe Ratio where the log-return is normally distributed. The second case subjects the log-returns to fat-tails. The third case subjects the log-returns to disasters while the fourth case subjects the log-returns to booms. We set the parameters so that the mean and variance of the log-return is the same across all cases. Inspite of the same mean and variance, Sharpe Ratio is the third case (disasters) is the highest, while the Sharpe Ratio in the fourth case (booms) is the lowest.

The model and the example are next.

II. The Model

This section introduces the model. The environment consists of two periods $t = \{0, T\}$, where $T$ is the length of time in years spanned by the two periods. There are two traded assets: a money market account with time $t$ value denoted by $B(t)$ and an index with time $t$ value denoted by $P(t)$. Without the loss of generality, we assume that the index does not pay any dividend.
The money market balance in the second period $T$ is

$$B(T) = B(0) \exp\{r_f\}, \quad (1)$$

where $r_f$ is the continuously compounded deterministic risk-free rate. The index price in the second period $T$ is

$$P(T) = P(0) \exp\{r\}, \quad (2)$$

with

$$r \equiv \mu + X - K(1). \quad (3)$$

The random variable $r$ representing the log-return is composed of two components. The first component $\mu$ is the average growth rate. The second component has two terms: it consists of a random variable $X$ less the Cumulant Generating Function (CGF) $K(1)$; where the CGF is defined as

$$K(\theta) \equiv \log \left[ \mathbb{E}\left[ \exp\{\theta X\} \right] \right] = \log \left[ \int_{-\infty}^{\infty} \exp\{\theta x\} dF_X(x) \right],$$

and $F_X(x) = \Pr[X \leq x]$ is the cumulative distribution function. The last term $K(1)$ is the convexity adjustment so that the expected index price in the second period $T$ is

$$\mathbb{E}\left[ P(T) \right] = \mathbb{E}\left[ P(0) \exp\{r\} \right] = \int_{-\infty}^{\infty} \exp\{\mu + x - K(1)\} dF_X(x) = P(0) \exp\{\mu\}. $$

Upon first glance, the two component structure may not seem familiar. However, as will be evident below, the structure simplifies the comparative statics later.

The CGF properties of the random variable $X$ can be better understood by expanding $K(\theta)$ as a power series in $\theta$ (around $\theta = 0$),

$$K(\theta) = \sum_{i=1}^{\infty} \kappa_i \frac{\theta^i}{i!} \quad \text{where} \quad \kappa_i \equiv \left. \frac{\partial^i}{\partial \theta^i} K(\theta) \right|_{\theta = 0}$$

\(^{2}\text{The domain of parameter} \ \theta \ \text{is set so that} \ K(\theta) < \infty.\)
is the \( i \)th cumulant of the random variable \( X \). Standard calculation shows that the first few cumulants are familiar. The first cumulant \( \kappa_1 \) is the mean; the second cumulant \( \kappa_2 \) is the variance; the third scaled cumulant Skew \( \equiv \kappa_3 / \kappa_2^{3/2} \) is the skewness and the fourth scaled cumulant Kurt \( \equiv \kappa_4 / \kappa_2^{2} \) is the excess kurtosis. Furthermore, as expected, there is a one-to-one mapping between moments of the random variable \( X \) and its cumulants. In this sense, just like moments, cumulants encompass all the information about the random variable \( X \).

The CGF of the log-return \( r \) is

\[
C(\theta) \equiv \log \left[ \mathbb{E} [\exp\{\theta r\}] \right] = \log \left[ \int_{-\infty}^{\infty} \exp\{\theta (\mu + x - K(1))\} dF_X(x) \right],
\]

\[= \theta \mu + K(\theta) - \theta K(1). \tag{4}\]

Denote the cumulants of the log-return \( r \) by \( c_i \). Due to the two component structure mentioned above, it turns out that all the cumulants except the first of the log-return \( r \) are identical to the cumulants of the random variable \( X \):

\[
c_1 \equiv \frac{\partial}{\partial \theta} C(\theta) \bigg|_{\theta = 0} = \mu - K(1) + \kappa_1; \quad \text{and} \quad c_i \equiv \frac{\partial^i}{\partial \theta^i} C(\theta) \bigg|_{\theta = 0} = \kappa_i \quad \forall i \geq 2.
\]

Then, the expected return of the index is

\[\mathbb{E} \left[ P(T) / P(0) \right] = \mathbb{E} \left[ \exp\{r\} \right] = \exp\{C(1)\},\]

and the variance of the index is

\[\text{Var} \left[ P(T) / P(0) \right] \equiv \mathbb{E} \left[ \left( P(T) / P(0) \right)^2 \right] - \mathbb{E} \left[ P(T) / P(0) \right]^2,
\]

\[= \exp\{C(2)\} - \exp\{2C(1)\},\]

with \( C(1) = \mu \) and \( C(2) = 2\mu + K(2) - 2K(1) \).
Lastly, the Sharpe Ratio is

$$SR \equiv \frac{\mathbb{E}[P(T) / P(0)] - \mathbb{E}[B(T) / B(0)]}{\sqrt{\text{Var}[P(T) / P(0)]}} = \frac{\exp\{C(1)\} - \exp\{r_f\}}{\sqrt{\exp\{C(2)\} - \exp\{2C(1)\}}}.$$  \quad (5)

Upon inspection, since

$$C(2) = \mu + \sum_{i=2}^{\infty} \frac{(2^i - 2) \kappa_i}{i!},$$

it is clear that the Sharpe Ratio in equation (5) depends on all the cumulants; i.e. $SR = SR(\{\kappa_i\}_{i \geq 2})$. Proposition 1 summarizes this observation.

**Proposition 1:** The Sharpe Ratio depends not only on the first two cumulants (mean and variance) but also on the higher cumulants.

We can get a better understanding of equation (5) by approximating the CGF of the random variable $X$ with a fourth-order polynomial:

$$K(\theta) = \kappa_1 \theta + \kappa_2 \theta^2/2 + \kappa_3 \theta^3/6 + \kappa_4 \theta^4/24.$$ 

With this approximation, CGF of the log-return $r$ evaluated at 2, $C(2)$, is

$$C(2) = 2\mu + \kappa_2 + \kappa_3 + 7/12 \kappa_4.$$ 

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3This approximation is closed related to the Gram-Charlier expansion. This type of expansion incorporates skewness and kurtosis and hence is often used as a tractable extension to the Normal distribution.
In turn, the Sharpe Ratio in equation (5) simplifies to

\[
SR \approx \frac{\exp\{\mu\} - \exp\{r_f\}}{\sqrt{\exp\{2\mu + \kappa_2 + \kappa_3 + 7/12 \kappa_4\} - \exp\{2\mu\}}} \\
\approx \frac{\mu - r_f}{\sqrt{\kappa_2 + \kappa_3 + 7/12 \kappa_4}}, \\
= \frac{\mu - r_f}{\sqrt{\kappa_2 (1 + \text{Skew} \sqrt{\kappa_2} + 7/12 \text{Kurt} \kappa_2)}}, \\
= SR^N \times \frac{1}{\sqrt{(1 + \text{Skew} \sqrt{\kappa_2} + 7/12 \text{Kurt} \kappa_2)}} \quad \text{with } SR^N \equiv \frac{\mu - r_f}{\sqrt{\kappa_2}}. \quad (6)
\]

In the second line, we use the approximation: \(\exp\{x\} \approx 1 + x\) and in the third line, we use the definition of skewness and kurtosis. We write \(SR^N\) to denote the Sharpe Ratio calculated assuming that the log-returns are normally distributed.⁴

Equation (6) describes the actual Sharpe Ratio \(SR\) as a product of two terms: the first term \(SR^N\) is the traditional term that depends on the mean and variance; the second term is the adjustment factor that depends on the skewness and kurtosis. The adjustment factor gives an insight of how higher cumulants affect the actual Sharpe Ratio \(SR\) relative to the traditional term \(SR^N\). Upon inspection of equation (6), it is clear that negative skewness increases the Sharpe Ratio and kurtosis decreases the Sharpe Ratio.

It turns out that the effect of skewness and kurtosis holds more generally. Differentiating \(SR(\{\kappa_i\}_{i \geq 2})\) with respect to the \(i\)th cumulant \(\kappa_i\) in equation (5) yields

\[
\frac{dSR(\kappa)}{d\kappa_i} = -\frac{1}{2} \times \frac{SR(\kappa)}{\text{Var}[P(T) / P(0)]} \times \exp\{C(2)\} \times (\frac{2^i - 2}{i!}) \times (1_{\kappa_i > 0} - 1_{\kappa_i \leq 0}), \quad (7)
\]

where \(1\) is the indicator function. Then, we have that

\[
\text{sign}\left(\frac{dSR(\kappa)}{d\kappa_i}\right) = -\text{sign}(\kappa_i).
\]

We summarize the implications of equation (7) in Proposition 2 and Corollary 1.

⁴Alternatively \(SR^N\) denotes the Sharpe Ratio that ignores higher cumulants of the log-return \(r\).
Proposition 2: Either even cumulants or positive odd cumulants decrease the Sharpe Ratio. Negative odd cumulants increase the Sharpe Ratio.

Corollary 1: Since returns subject to disasters have a negative third cumulant (negative skewness), they have a higher Sharpe Ratio than returns subject to booms. This is true even if both set of returns have the same variance and the same excess kurtosis.

Two examples help to clarify the effect of higher cumulants on the Sharpe Ratio.

Example 1: Log-return is NOT subject to either disasters or booms

Suppose the random variable \( X \) is normally distributed with zero mean and variance \( \sigma^2 \). Standard calculation shows that the CGF of the random variable \( X \), \( K(\theta) = \frac{1}{2} \sigma^2 \theta^2 \). Furthermore, the cumulants of the log-return \( r \) are

\[
c_1 = \mu - \frac{1}{2} \sigma^2; \quad c_2 = \kappa_2 = \sigma^2; \quad \text{and} \quad c_i = \kappa_i = 0 \quad \forall i \geq 3.
\]

Then the Sharpe Ratio becomes

\[
SR = \exp\{\mu\} - \exp\{r_f\} \approx \frac{\mu - r_f}{\sigma} \equiv SR_N. \quad (8)
\]

Equation 8 is the familiar equation of the Sharpe Ratio — it explicitly shows that the Sharpe Ratio depends on the first two cumulants (the mean and the variance) of the log-return.

Example 2: Log-return IS subject to either disasters or booms

The random variable \( X \) follows a two component structure:

\[
X = W + Z.
\]

The first component is normally distributed: \( W \sim N(0, \sigma^2) \). This component is the same as the one in Example 1. The second component \( Z \), the “jump” component, is a Poisson mixture of normals. That is, the number \( N \) representing the number of jumps is Poisson distributed with parameter \( \lambda \):

\[
Pr(N = n; \lambda) = \exp\{\lambda\} \lambda^n / n!.
\]
Conditional on the realization of \( N = n \), the jump component is normal:

\[
Z|n \sim \mathcal{N}(n \mu_J, n \sigma_J^2) \quad \forall \quad n = 0, 1, 2, \ldots.
\]

If the jump probability \( \lambda \) is small and if the average jump size \( \mu_J \) is large and negative, then the random variable \( X \) (and in turn the log-return \( r \)) is subject to rare disasters. Mathematically, skewness of the log-return is large and negative. In the same spirit, if the average jump size \( \mu_J \) is large and positive, the log-return is subject to rare booms and exhibits large and positive skewness. Lastly, if the average jump size \( \mu_J \) is zero and if volatility conditional jumps \( \sigma_J \) is large, the log-return is subject to tail-risk and exhibits zero skewness and large kurtosis.

The two component structure is a one period formulation of the jump diffusion model in Merton (1976). The CGF of the random variable \( X \) is

\[
K(\theta) = \frac{1}{2} \theta^2 \sigma^2 + \lambda \exp\{\theta \mu_J + \frac{1}{2} \theta^2 \sigma_J^2\}.
\]

In turn, the first few cumulants of the log-return are

\[
\begin{align*}
c_1 &= \mu - K(1) + \kappa_1, \quad \text{with} \quad \kappa_1 = \lambda \mu_J; \\
c_2 &= \kappa_2, \quad \text{with} \quad \kappa_2 = \sigma^2 + \lambda (\mu_J^2 + \sigma_J^2); \\
c_3 &= \kappa_3, \quad \text{with} \quad \kappa_3 = \lambda \mu_J (\mu_J^2 + 3 \sigma_J^2), \quad \text{and Skew} = c_3 / c_2^{3/2}; \\
c_4 &= \kappa_4, \quad \text{with} \quad \kappa_4 = \lambda (\mu_J^4 + 6 \mu_J^2 \sigma_J^2 + 3 \sigma_J^4), \quad \text{and Kurt} = c_4 / c_2^2.
\end{align*}
\]

Note that the sign and magnitude of the cumulants of the log-return reflect a complex combinations of parameters. For example, the sign of the skewness depends on the sign of the average jump size \( \mu_J \) but the magnitude depends on the probability of disasters \( \lambda \), the average jump size \( \mu_J \) and the volatility conditional on jumps \( \sigma_J \).

We can see the effect of higher cumulants on the Sharpe Ratio \( SR \) in Table I. This Table has four columns corresponding to four different cases. The first column describes the case

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\[5\)This formulation is also used in the macro-economics literature to explain the equity premium puzzle. See Martin (2013) for a survey of the literature regarding disasters and the equity premium puzzle.
in Example 1 where the log-return is not subject to any disaster or boom. The second column describes the case where the log-return is subject to tail-risk. Note, that the tail-risk is symmetric — there is equal probability of both disasters and booms which leads to zero skewness.

The third column describes the case where the log-return is subject to rare disasters. The average jump size $\mu_J$ is set to -99% — a disaster effectively wipes out the investment in the index. Since $\mu_J$ is large and negative, skewness is also large and negative (-10.61) while kurtosis is large (154.24). This case reflects an option based strategy that shorts out of the money calls and puts. Since options are out of the money, most of the time, the short positions will expire without any negative implications. However, in a rare case, the options will incur huge losses.

In the same spirit, the fourth column describes the case where the log-return is subject to rare booms. The average jump size $\mu_J$ is set to 99% — a boom effectively doubles the investment in the index. Since $\mu_J$ is large and positive, skewness is also large and negative (10.61) while kurtosis is large (154.24). This case reflects an option based strategy that longs out of the money calls and puts. This strategy will double investment rarely while most of the time, this strategy will lose option premiums.

In all cases, we set the risk-free rate to 2%. Lastly, we set the parameters so that the first two cumulants of the log-return are equal across all the cases.

Consider the first column, the benchmark case of no disasters or booms. The actual Sharpe Ratio $SR$ and the traditional term $SR^N$ — “normal” approximation — are identical; they both equal 0.50. This is expected as the adjustment factor is equal to one since both skewness and kurtosis are zero. In fact, the $SR^N$ does not vary too much across all the cases — the range is between 0.48 and 0.55. This is also expected as the parameters are chosen so that the first two cumulants of the log-return are the same across all the cases.

Now, consider the second column, the case of tail-risk. The actual Sharpe Ratio $SR$ is about 57.67 % lower than the traditional term $SR^N$. This is also clear from the adjustment factor. Since the skewness is zero and kurtosis is high, adjustment factor is less than one. Now, consider the third column, the case of rare disasters. The actual Sharpe Ratio $SR$ is about 36.99 % higher than the traditional term $SR^N$. Since the skewness is negative, adjustment
factor is more than one. The most dramatic departure arises in the fourth column representing rare booms. The actual Sharpe Ratio $SR$ is about 207.85 % lower than the traditional term $SR^N$. Since the skewness is positive and kurtosis is high, adjustment factor is significantly less than one.

To summarize, Table I summarizes the effect of cumulants on the Sharpe Ratio. The implications for an investor or an asset manager are clear. For instance, suppose that the asset manager is judged on the basis of the Sharpe Ratio. Then the asset manager will choose an investment strategy in which the log-return will be subject to disasters. That is, it is in the best interest of the asset manager (if allowed) to short options. Empirically, this type of investment strategy is consistent for a variety of hedge funds [Agarwal and Naik (2004)].
Table I: This table calculates the Sharpe Ratio for four different cases. Column (1) is the benchmark case: log-returns are not subject to any disasters or booms. Column (2) describes a case in which log-returns are subject to symmetric tail risk. Column (3) describes a case in which log-returns are subject to rare disasters. Column (4) describes a case in which log-returns are subject to rare booms. In all the cases, the parameters are chosen so that the first two cumulants (mean and volatility) of the log-returns are equal. Variable SR denotes the actual Sharpe Ratio that takes all the cumulants into account. Variable $SR^N$ denotes the “normal” Sharpe Ratio that only considers the first two cumulants. Variable Rel-Diff shows the relative difference between the two Sharpe Ratios. Finally, the risk free rate is 2.00% in each case.

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