The impact of downside risk on risk-adjusted performance of mutual funds in the Euronext markets.

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Comments Welcome
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Abstract
Many performance measures, such as the classic Sharpe ratio have difficulty in evaluating the performance of mutual funds with skewed return distributions. Common causes for skewness are the use of options in the portfolio or superior market timing skills of the portfolio manager. In this article we examine to what extent downside risk and the upside potential ratio can be used to evaluate skewed return distributions. In order to accomplish this goal, we first show the relation between the risk preferences of the investor and the risk-adjusted performance measure. We conclude that it is difficult to interpret differences in the outcomes of risk-adjusted performance measures exclusively as differences in forecasting skills of portfolio managers. We illustrate this with an example of a simulation study of a protective put strategy. We show that the Sharpe ratio leads to incorrect conclusions in the case of protective put strategies. On the other hand, the upside potential ratio leads to correct conclusions. Finally, we apply downside risk and the upside potential ratio in the process of selecting a mutual fund from a sample of mutual funds in the Euronext stock markets. The rankings appear similar, which can be attributed to the absence of significant skewness in the sample. However, find that the remaining differences can be quite significant for individual fund managers, and that these differences can be attributed to skewness. Therefore, we prefer to use the UPR as an alternative to the Sharpe ratio, as it gives a more adequate evaluation of the use of options and forecasting skills.

Introduction

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In this article we study the performance of mutual funds from the perspective of an investor who considers selecting one from a large universe of mutual funds. Most of the literature on this topic is developed from the Capital Asset Pricing Model and focuses on risk-adjusted performance measures. such as the Sharpe ratio and Jensen's alpha. These have become quite popular in academic research as well as practical applications. These measures rely on the assumption that returns are normally distributed. In academic research, differences between the outcomes of these measures for different portfolio managers are often interpreted as differences in the forecasting skills between these managers.

Bookstaber and Clarke [1984] and Dybvig and Ross [1985] showed that the assumption of normality is crucial in order to facilitate this interpretation of the risk-adjusted performance measures based on CAPM. For example, a portfolio with stocks and put options results in a return distribution that is positively skewed. Indeed, as has been shown by Bookstaber and Clarke [1984] and more recently by Leland [1999], the risk-adjusted performance of portfolios with options depends on the amount of options included. They showed that an uninformed investor can increase his Sharpe ratio above that of the market index by adding call options to a portfolio based on the market index.

Even without options in the portfolio the assumption of normality can be violated in a way that prohibits interpretation of the performance measures in terms of forecasting skills. Surprisingly, this violation is the result of the portfolio choices made by an informed investor. For example, Dybvig and Ross [1985] and Merton [1981] showed that investors with market timing information create portfolios with returns that do not follow a normal distribution.

These violations of normality make it difficult to interpret the differences in risk-adjusted performance measures as differences in forecasting skills. From the perspective of an investor who considers investing in a portfolio with a particular return distribution, the forecasting abilities of the portfolio manager may be of secondary choice. His primary concern is the shape of the return distribution, and only to a lesser extent he will be interested in the process that created this distribution. Therefore, we choose an alternative interpretation based on preference functions to measure risk-adjusted performance. We interpret the outcome of a risk-adjusted performance measure as the expected value of a preference function. The outcome of the risk-adjusted performance measure represents the attractiveness of the investment and is not a measure of the forecasting skills of the portfolio manager.

This interpretation of a performance measure is different from that of the management of an investment management company that is interested in monitoring and controlling the investment process. As part of the management and control process, they will be interested in measuring the factors that contributed to the performance as well. Other authors also interpreted performance measures as preference functions. For example, Stutzer [2000] develops a performance indicator that is based on an exponential utility function.

In this article, we study the properties of the Sharpe ratio and the upside potential ratio (see Sortino, van der Meer, and Plantinga [1999]). The Sharpe ratio uses standard deviation as a measure of risk, whereas the upside potential ratio uses downside deviation as a measure of risk. Downside deviation explicitly incorporates part of the preference function of the investor by including a minimal acceptable rate of return (MAR). We claim that downside risk is able to overcome the problems with ranking investment opportunities with skewed return distributions.

First, we discuss the relationship between preference functions and the risk-adjusted performance measures. We conclude that the use of measures based on downside deviation is associated with preference functions that model the risk attitude relative to a reference rate of return. Next, we investigate the properties of the Sharpe ratio and the upside potential ratio in the context of a simple simulation study of an investor considering to buy portfolio insurance. We find that the upside potential ratio is better able to measure the performance of an investor aiming for put protection. Finally, we examine the differences between the Sharpe ratio and the upside potential ratio in ranking a sample of mutual funds. In order to attain this goal, we selected a sample of European mutual funds from the Euronext markets.

Risk-adjusted performance measures and preference functions

In this section we examine the relation between risk measures, risk-adjusted performance measures, and preference functions. We start with a discussion of the classic capital asset pricing model (CAPM), which is rooted into utility theory. Next we discuss a more general class of preference functions proposed by Jia and Dyer [1996] that can be used to model risk attitudes relative to a reference rate.

Mean variance theory
Modern portfolio theory and in particular CAPM introduced the idea of a formal relationship between risk and return as a result of market equilibrium conditions. A logical application of the formal link between risk and return was in the evaluation of the returns of managed portfolios. This resulted in the introduction of risk-adjusted performance measures by Jensen [1968], Treynor [1966], and Sharpe [1966].

CAPM is an equilibrium theory of asset prices and can be justified by either of the following assumptions:

1. The returns of assets are normally distributed.
2. The investors have quadratic utility functions.

Consequently, it is possible to replace the assumption of normality with that of quadratic utility. In our introduction, we expressed doubts and cited evidence against the assumption of normality of the return distribution, and in particular, to the consequences for risk-adjusted performance measures. Therefore, the use of risk-adjusted performance measures based on CAPM needs to be motivated by the assumption of quadratic utility. The main objection against the use of a quadratic utility is that at a sufficient high level of wealth, the utility of an additional unit of wealth is decreasing. This seems to be a very unlikely property for the utility of wealth. However, in practice it is possible to construct a utility function model in such a way that this part of the domain of the utility function will not be used for realistic return distribution.

The relation between preference functions and risk-return measures is discussed in Jia and Dyer [1996]. They introduced a risk-value model that integrates risk measures directly into decision models. In other words, a risk-value model is shown to be equivalent to a preference model. An important condition for the use of a risk-value model is the risk independence condition.

> *Risk independence condition*
>
> A risk-value model satisfies the risk independence condition if an individual prefers alternative *x* over *y* for any level of wealth, given that the expected value of both alternatives is equal to zero.

Jia and Dyer [1996] show that the quadratic utility function is one of the two continuously differentiable utility functions that can be represented in the form of a separable risk-value model. In other words, the expected value of a quadratic utility function $U = W - bW^2$, can be rewritten in terms of return and standard deviation as follows:

$$E[U(W)] = \alpha - \beta\sigma_r^2 , \qquad (1)$$

where α and β can be written as a function of initial wealth W_0, the expected return $E[r]$, and the parameter b from the quadratic utility function in terms of terminal wealth in the following way:

$$\alpha = (1 + E[r])(W_0 - bW_0^2)$$
$$\beta = bW_0^2 .$$

Equation (1) shows that variance or standard deviation is a risk measure that logically associates with a quadratic utility function. Jia and Dyer prove that equation (1) is the only way to represent the quadratic utility function in term of mean and variance. As the Sharpe ratio is not consistent with this function, it is also not consistent with a quadratic utility function[1]. This has also been shown by Plantinga and De Groot [2001], who ranked the performance of 105 mutual funds based on the Sharpe ratio, and compared this with rankings based on quadratic utility functions. By maximizing the rank correlation coefficient between the Sharpe ranking and the utility based ranking, they tried to solve for the optimal value of b. The highest achievable rank correlation was equal to 79%.

Downside risk

Frank Sortino recognized the relevance of introducing investor's risk preferences into performance measures with the introduction of the downside risk concept into the performance measurement literature. Downside risk incorporates the risk preferences of the investor by introducing a minimal acceptable rate of return (MAR), which represents the objective of the investor. Good volatility (above the MAR) is distinguished from Bad volatility (below the MAR). Therefore, volatility per se, is not synonymous with risk.

Downside risk is a measure related to the lower partial moments framework (Bawa and Lindenberg [1977]). The n-th order lower partial moment of a random return r with distribution F and with respect to a reference point k is defined as:

$$LPM_n \equiv \int_{-\infty}^{k} (k - r)^n \, dF(r) , \tag{2}$$

Downside risk as defined by Sortino is the second partial moment with respect to the MAR. Here, we write downside risk in terms of a discrete distribution of r based on a time series of returns:

$$\delta_{mar} = \sqrt{\sum_{t=1}^{T} t^+ p_t (r_t - r_{mar})^2} \tag{3}$$

where t is an index of the observation, r_t is the return in month t, $p_t = 1/T$ is the probability of an observation, and r_{mar} is the MAR. An important advantage of the downside risk measure is that it also captures a-symmetries with respect to the reference point.

Jia and Dyer [1996] show that downside risk is associated with the following piecewise linear plus power preference function:

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[1] The definition of the Sharpe ratio used by practitioners is usually $S = \frac{E[r] - r_f}{\sigma}$. Sharpe [1994] aims at a more general definition that facilitates the use of the Sharpe ratio as a statistic to test for the outperformance against any benchmark.

$$u(x)=\begin{cases} ax+x^{\alpha} & if\, x\geq 0 \\ ax-\lambda|x|^{\beta} & if\, x<0 \end{cases}, \tag{4}$$

where $a \geq 0$ and α, β, and λ are constants. From this preference function, they derived the so-called standard model of risk, which shows that downside risk is a risk measure consistent with this preference function if $\lambda=1$ and $\beta=2$:

$$R(x') \equiv \lambda E^{-}\left[\left|x-E[x]^{\beta}\right|\right]-E^{+}\left[|x-E[x]|^{\alpha}\right] \tag{5}$$

This standard model of risk shows that the benefits of a return distribution can be measured with the right hand side of the equation. For example, the benefits can be measured as the so-called upside potential with α=1.

Sortino, Van der Meer and Plantinga [1999], suggested the idea of evaluating upside potential against downside risk, called the upside-potential ratio (UPR)[2] . The UPR is defined as follows:

$$UPR_{mar} \equiv \frac{UP_{mar}}{\delta_{mar}} = \frac{\sum_{t=1}^{T} \iota^{+} p_t (r_t - r_{mar})}{\sqrt{\sum_{t=1}^{T} \iota^{-} p_t (r_t - r_{mar})^2}}, \tag{6}$$

with ι^{-} = 1 if $r_{p,t} \leq r_{mar}$, ι^{-} = 0 if $r_{p,t} > r_{mar}$, ι^{+}=1 if $r_t > r_{mar}$, and ι^{+} = 0 if $r_t \leq r_{mar}$.

We propose to use the UPR as an alternative for the Sharpe ratio. The measure differs from the Sharpe ratio in two ways. First, it allows the user to model the risk-preferences consistent with Jia and Dyer's standard model of risk, measuring risk relative to a reference point. Second, the measure is better able to capture a-symmetries in the return distribution.

To illustrate the potential advantages of the upside potential ratio, let's assume an investor has an initial wealth equal to 100 and needs to have at least 100 at the end of the period. In other words, this investor has a minimal acceptable rate of return equal to 0%. The investor considers constructing a portfolio of risky assets consisting of an index fund and a European put option on the index fund. Furthermore, it is given that the risk-free rate is equal to 5%, the index fund has an expected annual return equal to 10% and that the index fund has an annual standard deviation of 20%.

Using a protective put strategy, the investor can accomplish this goal by buying a put option on the index fund. Suppose that the initial value of the index is equal to 100. Then, according to the Black and Scholes model, the price of a put option on this index with a strike price equal to 111.5 is approximately equal to 11.59[3]. This strategy yields a return that is at least 111.5 / (100+11.59) ≈ 0%. If the investor decides to invest in this strategy he is able to meet his goal of attaining a return equal to at least 0%.

Using Monte Carlo simulation, we constructed a distribution of the returns from this strategy. We constructed 1000 random draws from a normal distribution with an expected return of 10% and a standard deviation of 20%. We calculated the terminal value of the strategy, and performance statistics, such as the average return, the Sharpe ratio, and the UPR. For the protective put strategy

[2] Practitioners also use the Sortino ratio (see Sortino & Price[1994]), which is defined as: $Sortino = \frac{E[r]-r_{mar}}{\delta_{mar}}$.

The upside potential ratio is different from the Sortino ratio as it's numerator only involves the returns above the minimal acceptable rate of return.

[3] As we do not want to focus on the details of options pricing and portfolio insurance, we simplified the example by assuming that the index does not pay any dividends.

matching an appropriate MAR is 0%. We find that the average return is 6.67%, standard deviation is 10.2%, downside deviation is 0%, the Sharpe ratio is equal to 0.164, and the UPR is 117.9.

Table 1: The outcomes of protective put strategies with different levels of protection.

Maximum loss	**σ**	**Skewness**	**δ_0**	**UPR_0**	**Sharpe**
35.0%	19.8%	8.2%	8.57%	1.670	0.282
12.0%	17.1%	57.9%	5.48%	2.275	0.269
2.0%	12.1%	137.7%	1.32%	6.222	0.195
0%	10.2%	173.7%	0.06%	117.9	0.164
-1.0%	9.0%	203.5%	0.00%	+∞	0.138

Given our MAR of 0%, the protective put strategy specified in our example is a good way of avoiding all risks of falling below the target[4]. In Table 1 we present the outcomes of our simulation study for protective put strategies with alternative levels of put protection. In the first column we present the floor relative to the current wealth level. The second and the third column present the standard deviation and the skewness. As can be seen, standard deviation decreases with the level of put protection. We also see that skewness increases with level of put protection. In the fourth column, downside deviation is calculated using a minimal acceptable rate of return of 0%. As expected, downside deviation decreases with the level of put protection. The next column presents the UPR, which increases with the level of put protection, as opposed to the Sharpe ratio (last column), which is decreasing with the level of put protection.

This example illustrates that an investor who specifies an investment goal in term of a minimum acceptable return and buys put protection, should not use the Sharpe ratio as an indicator of his success. *The better the investor is able to attain his goal, the lower the Sharpe ratio*. Furthermore, this example confirms Bookstaber and Clarke's conclusion that the Sharpe ratio cannot be used as a measure of forecasting skills if the investor uses options. The upside potential ratio is superior in this situation, as it increases with the level of put protection. Of course, as soon as the desired level of put protection is attained, downside deviation equals zero, and the UPR cannot be used to distinguish between two alternatives with different levels of upside potential. Therefore, riskless strategies should be ranked by upside potential alone.

Data

In order to investigate the differences between the Sharpe ratio and the UPR in an empirical setting, we collect data on mutual funds were obtained from the Standard & Poor's Micropal database on European mutual funds. We collected 72 monthly observations of total rate of return for funds in Belgium, France, and the Netherlands from January 1994 until December 1999. The stock exchanges of these countries announced in 2000 a merger resulting in the EURONEXT, which is competing in size with the exchanges of London and Frankfurt.

Table 2: Characteristics of the mutual funds sample

	# funds (1/1/00)	# funds (1/1/94)	P(≤ 0.80)	E[r]*	σ**
Belgium	759	186	103	0.94%	4.56%

[4] In our analysis, we ignore alternatives for the protective put strategy. For example, dynamic strategies such as contingent proportion portfolio insurance (Perold and Sharpe [1988]) or contingent immunization (Hakanoglu, Kopprasch and Roman [1989]) could also attain the desired level of protection.

France	*SICAV*	1,392	938	345	0.77%	4.74%
	FCP	2,292	832	270	0.84%	4.82%
Netherlands		447	148	92	0.85%	5.37%
Total		4,890	2,104	810	0.82%	4.81%

* Statistics are calculated based on the monthly observations of returns over the period January 1994 to December 1999 measured in terms of local currency returns (until 31/12/1998) and Euro (starting from 1/1/1999).

** Average standard deviation of funds in the sample.

Table 2 gives the key characteristics of the funds. We chose to select those funds with a return history of 72 months as a compromise between a very limited selection of funds with a very long return history and a large selection of funds with a very short return history.
As we want to focus on funds with higher volatility and a more diverse behavior, we decided to omit funds with a large exposure to bonds and money market instruments from the analysis. Therefore, based on the style regression specified in equation (7), we omitted those funds with an exposure to bonds of 80% or more. Many mutual funds in Belgium and France had a double entry in the database, as they are sold through different distribution channels. We also omitted these double entries. As a result the number of selected funds was reduced from 2104 to 810.

The average returns and standard deviations of the selected funds are also shown in Table 2. The average monthly returns are highest in Belgium and lowest in France. The volatility in the returns is highest in the Netherlands. In France two legal forms of mutual funds exist: SICAVs and FCPs. A SICAV ("Société d'Investissement à Capital Variable") is an investment company with variable share capital. A mutual fund that has a SICAV structure is an independent legal entity with its own set of articles of incorporation and its own Board of Directors. Each share in the SICAV entitles the shareholder to a voting right at any shareholders meeting of the SICAV. A FCP ("Fonds Commun de Placement") is not an independent legal entity. A management company manages it and the unit holders have no vote and therefore cannot take control of the company. The decisions lie with the board and the shareholders of the management company.

To analyze the performance statistics with respect to different asset classes, we performed returns based style analysis using equation (7). In this equation, the return of a mutual fund is determined by market indices using a constrained regression analysis.

The return of mutual fund i in month t is:

$$R_{i,t} - r_{f,t} = \alpha_i + \sum_{j}^{J} b_{ij}\left(r_{j,t} - r_{f,t}\right) + e_{i,t}, \qquad (7)$$

where the coefficients are solved from minimizing the sum of the squared errors subject to:

$$b_{ij} \geq 0$$

$$\sum b_{ij} = 1$$

In Table 3 we present the market indices used as the factors j in regression equation (7). As can be seen from this table, the MSCI pacific index yielded a negative performance during this period, while the US growth index generated the highest return. Furthermore, it should be noted that both value indices exhibit considerable negative skewness, whereas the Pacific index exhibits positive skewness.

Table 3: Market indices used for style regression

	E[r]	**σ**	**Skewness**	**Ddev**	**UPR**
SB WGBI	0.01%	3.72%	0.134	2.61%	0.542
MSCI Pacific	-0.09%	6.17%	0.258	4.26%	0.566

MSCI Europe Growth	1.04%	4.50%	-0.025	2.67%	0.867
MSCI Europe Value	1.03%	4.55%	-0.601	2.94%	0.789
MSCI US Growth	1.76%	4.43%	-0.311	2.43%	1.134
MSCI US Value	1.04%	4.15%	-0.685	2.61%	0.831

In Table 4 we present the outcomes of the style analysis. Notice that the Dutch mutual funds have more assets invested outside Europe (35.4%) than the Belgian funds (19.9%) and the French funds (15.8% and 19.7%). During this period, European mutual funds had a higher exposure to the European growth index than to European value index. With respect to the US, the opposite seems to occur: European mutual funds prefer a higher exposure to the US value index.

Table 4: average style exposure

	WGBI	Pacific	Europe Growth	Europe Value	US Growth	US Value	Avg. R^2
Belgium	30.7%	7.2%	29.2%	20.4%	5.5%	7.2%	77.1%
France FCP	22.7%	9.1%	36.8%	24.7%	2.3%	4.4%	65.2%
France Sicav	17.6%	10.7%	39.9%	22.9%	4.0%	5.0%	72.8%
Netherlands	23.7%	19.5%	22.7%	18.2%	7.2%	8.7%	65.4%
All funds	22.1%	10.6%	35.3%	22.8%	3.8%	5.4%	69.3%

Results

In this section we use the upside potential ratio (UPR) to rank the mutual funds in our sample. The minimal acceptable rate of return (MAR) is an important determinant in ranking mutual funds using the UPR. Therefore, we start our analyses with examining the differences between downside risk and standard deviation. In order to do so, we choose the MAR equal to the mean of the distribution. We denote this special version of downside risk as $\delta_{E[r]}$. If r follows the normal distribution, and the MAR is equal to the mean of the return distribution, then downside risk and standard deviation will result in an equal ranking. As downside risk captures only the negative deviations, we need to add the upside deviations in order to get exactly the same number. So, given a symmetrical return distribution the following deterministic relation between standard deviation and downside applies:

$$\sigma_r = \sqrt{2}\delta_{E[r]}. \qquad (8)$$

As a result, downside risk ranking based on the mean should be equal to the ranking based on standard deviation. The rank correlation coefficient between downside risk and standard deviation turns out to be 96.5%. Table 5 shows us that on average the value of our adjusted downside risk measure is slightly lower than the standard deviation. In other words, standard deviation on average overestimates the risk of the individual fund. By calculating the downside risk measure with respect to the mean, the only differences in ranking with the standard deviation is due to the fact that the empirical distribution deviates from the normal distribution. Therefore, our results indicate that the upside volatility with respect of the mean is somewhat larger than the downside volatility, which indicates that the return distributions are somewhat positively skewed.

Table 5: A comparison of downside deviation with standard deviation

	σ	$\delta_{E[r]}$	P (σ > $\delta_{E[r]}$)	P(skw>0)
Growth	4.8%	4.8%	60.0%	54.7%

Value	5.3%	5.4%	39.3%	31.5%
Bonds	4.4%	4.4%	32.9%	37.2%
Pacific	7.1%	6.7%	93.3%	90.0%
Mixed	4.8%	4.8%	36.6%	35.7%
All Funds	5.0%	4.9%	49.1%	46.5%

A striking result in Table 5 is that almost all Pacific funds have positive skewness, and have also on average the largest difference between the standard deviation and the adjusted downside risk measure. We checked to see if this result holds at the individual fund level. For all funds with a standard deviation exceeding the adjusted downside risk, we find that 90.1% of the also have positive skewness. Therefore, we conclude that the difference between standard deviation and the adjusted downside risk is caused by skewness. Furthermore, the direction of skewness is not equal for all fund styles. In particular, value funds, bond funds, and mixed funds exhibit negative skewness.

As we intend to use the risk measures in risk-adjusted performance measures, we calculated both the Sharpe ratio and two versions of the UPR. As pointed out by Sharpe [1994], the Sharpe ratio can be interpreted as a test for outperformance against a benchmark. In case of the classic Sharpe ratio with the risk-free as benchmark, the Sharpe ratio provides a test for how well the risky return performance in comparison with the risk-free rate. In the spirit of this interpretation we calculated the UPR with a MAR of 0% (UPR_0) and with a MAR equal to the risk-free rate in each of the three countries in our sample (UPR_{rf}). Like the Sharpe ratio, UPR_{rf} can be interpreted as a test of the performance of the mutual fund in comparison with the risk-free rate.

We calculated the calculated the rank correlation between the Sharpe ratio and the UPR. This correlation is 97.2% for the UPR_{rf} and 97.6% for the MAR_0. Stutzer [2000], who also developed a performance indicator accounting for skewness in returns, also found a very high correlation when comparing his performance index with the Sharpe ratio. However, we do not believe that the choice between the Sharpe ratio and the UPR is trivial. As we showed with our simulation study, the correlation between the Sharpe ratio and the UPR can be negative with portfolio insurance strategies. We attribute the high correlation between the Sharpe and the UPR in the sample of Euronext mutual funds to the fact that most return distributions are normal. We performed a Jarque-Bera test for normality on each of the individual fund return distribution, and we cannot reject normality in 90.5% of the funds in our sample at a confidence level of 95%.

Skewed returns distributions can arise from either market timing skills (Merton [1981]) or the use of call options (Bookstaber and Clarke [1984]). Therefore, we conclude that the majority of the fund managers in the Euronext sample does not have market timing skills or employ options. Nevertheless, an appropriate risk-adjusted performance indicator should be able to select such managers if they show up at some time in the future. However, even in the context of the Euronext sample, the impact of not being able to capture skewness can already have serious consequences for individual fund managers. In order to stress the importance of this point, we investigated the differences in ranking between the Sharpe ratio and UPR_{rf}. First we calculate the difference in ranking based on the Sharpe ratio and the UPR_{rf} as:

$$DIFRANK_i \quad = \quad RANKNR(Sharpe) - RANKNR(UPR_{rf}) \qquad (8)$$

In Table 6 we present the relative frequencies of these differences in rank number. A negative number means that the fund is ranked higher in terms of the upside potential ratio as compared to the Sharpe ratio. From this table, we deduce that 87.4% of the ranking differential refers to a deviation from –98 to + 78 places on the ranking. So despite the fact that the rank correlation of 97.2% suggests that the rankings are almost the same based on statistical grounds, the differences may be considerable from the perspective of an individual fund manager.

Table 6: Relative frequencies of difference in ranking between Sharpe and UPR_{rf}

Interval			Relative frequency
	< x ≤	-276	0.1%
-276	< x ≤	-217	0.2%
-217	< x ≤	-157	0.5%
-157	< x ≤	-98	3.9%
-98	< x ≤	-39	15.7%
-39	< x ≤	20	48.2%
20	< x ≤	79	23.5%
79	< x ≤	139	6.9%
139	< x ≤	198	0.8%
198	< x ≤		0.2%

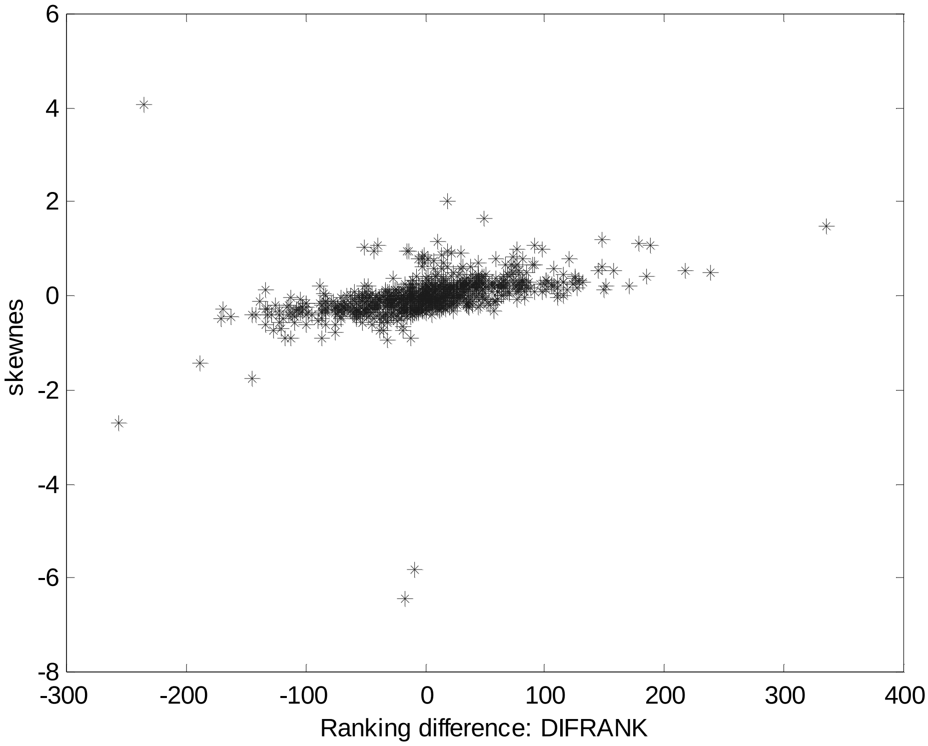
Based on our earlier results, we expect that these differences in ranking are caused by skewness. Therefore, we plotted in Figure 1 the variable DIFRANK against the level of skewness in the return distribution of the mutual fund. As can be seen from this figure, there is a positive relation between the difference in ranking and skewness. In particular, omitting the extreme values of skewness above 4 and below minus 4 results in a very robust linear relation.

Table 7: Outcomes of regression model

	with outliers		without outliers	
		t-stat		t-stat
Alpha	-0.0147	(-0.981)	-0.0063	(-0.665)
Beta	0.0035	(13.5)	0.0038	(23.33)
R^2	17.48%		39.02%	
DW	1.97		1.91	
	n=810		n=807	

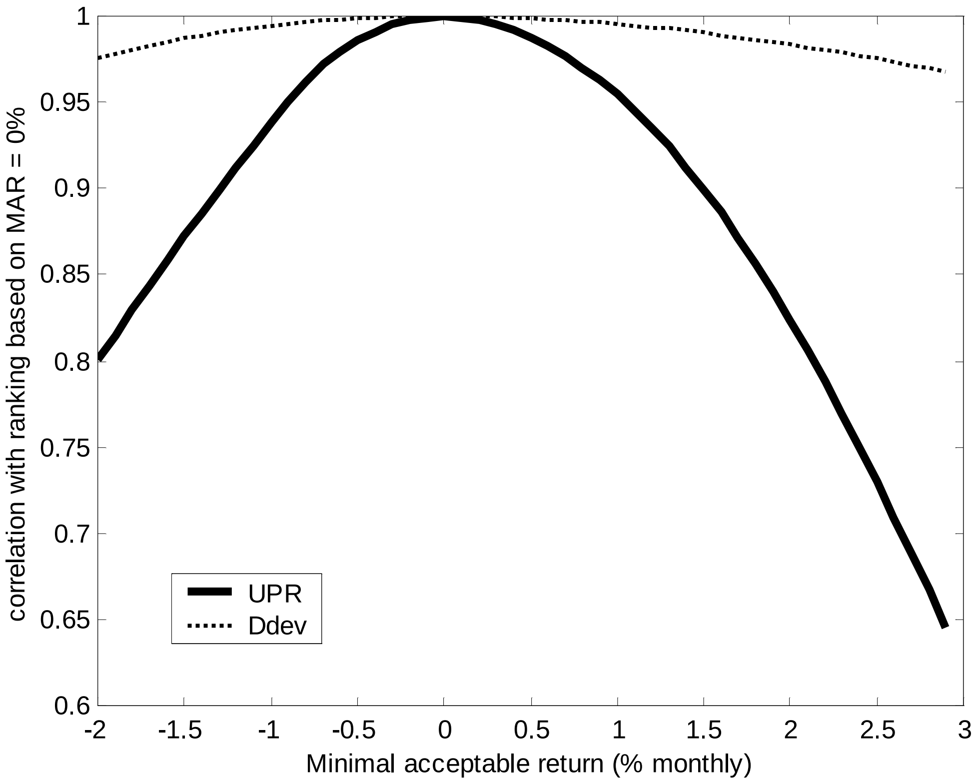
In Table 7 we estimated the regression line using OLS, including and excluding the three outliers. As can be seen, in both cases the slope of the regression line is highly significant. The percentage of explained variance indicates that a considerable part of the differences in ranking can be attributed to the differences in skewness.

Figure 1: Scatter plot of ranking differential and skewness of return distribution



In figure 2 we present the rank correlation coefficients between rankings based on downside deviation and the UPR with different levels of minimal acceptable return. We calculated the correlation relative to a ranking of the Euronext funds based on a MAR of 0%. The MAR is plotted on the horizontal axis and ranges from –2% to +3% on a monthly basis. As can be seen in this figure, the calculation of downside deviation is not very sensitive to the choice of the MAR. All correlation coefficients are well above 95%, even for very different MARs. On the other hand, the upside potential ratio seems to be affected more by the choice of the MAR. However, even a monthly MAR of 1% that translates into an annual average return of 12% results only in a rank correlation slightly above 0.90. These results suggest that the choice of the MAR is less relevant. Again, we refer to our earlier conclusion that the deviations from normality in our sample is not big enough to generate different rankings.

Figure 2: The impact of the minimal rate of return on downside deviation and the upside potential ratio.



Finally, we investigate whether the performance of the mutual fund differs across investment styles and countries of origin. We use the outcomes of the style analysis to classify the investment styles. All funds with a total exposure to both growth indices exceeding 50% classify as growth funds. Similarly, we classify the value style funds, the bond funds and the pacific funds. Finally, all remaining funds classify as mixed funds. In table 7 we present the average outcomes of the performance measures for the different styles.

Table 8: Risk-adjusted performance for different investment styles

	Sharpe	**Upr_{rf}**	**Upr_0**	**E[r]**	**UP_0**	**δ_0**
Growth	17.48%	77.75%	90.38%	1.20%	2.50%	2.79%
Value	9.55%	65.60%	76.03%	0.76%	2.37%	3.42%
Bonds	2.67%	58.20%	69.40%	0.44%	1.94%	2.89%
Pacific	-0.01%	57.97%	64.60%	0.37%	2.88%	4.52%
Mixed	9.13%	65.98%	77.57%	0.71%	2.21%	3.01%
All Funds	10.50%	68.39%	79.80%	0.82%	2.34%	3.06%

An interesting result is that the differences between the five classes in terms of performance are bigger in terms of the Sharpe ratio, whereas both upside potential ratios yield much smaller differences between asset classes. Although this may be considered a scaling issues, it also is related to the skewness issue. Studying the funds with exposure to the Pacific, it is remarkable that the pacific funds score worst on all of the criteria except for the upside potential. Positive skewness results in a higher upside potential. In the Sharpe measure this is captured partly in the expected return, but most of it is accounted for as higher volatility and thus higher risk.

Conclusion

In this article we discussed the impact of downside risk on risk-adjusted performance evaluation. We concluded that it is difficult to interpret differences in the outcomes of risk-adjusted performance measures exclusively as differences in forecasting skills of portfolio managers. Therefore, we choose to interpret a risk-adjusted performance measure as an alternative to a preference function. As has been shown by Jia and Dyer [1996], a piecewise linear plus power preference function can be used to represent the preferences of an investor whose preferences changes relative to a minimal acceptable rate of return (MAR). In this spirit of this preference function, we previously developed the so-called upside potential ratio (UPR).

As an example we showed that a protective put strategy can be a suitable strategy for an investor whose preferences are described relative to a MAR. Using a simple Monte Carlo simulation, we showed that protective put strategies with guaranteed rates below the MAR of our investor resulted in higher Sharpe ratios than those of the strategies with guaranteed rate above the MAR. On the other hand, the UPR was increasing with the level of the guaranteed rate. A well-known property of a protective put strategy is that it results in a positively skewed return distribution. The skewness increases with the guaranteed level. Apparently, the UPR is better able to capture this skewness, so we concluded that the UPR is more suitable as an evaluation criterion than the Sharpe ratio for investors seeking downside protection.

Next, we studied the relevance of downside risk and the UPR in the process of selecting a mutual fund. We used a sample of mutual funds in the Euronext stock markets. In order to make a fair comparison between the Sharpe ratio and the UPR, we used a MAR equal to the risk-free rate. We constructed a ranking based on both criteria, and we find a very high correlation between the Sharpe ratio and the UPR. This is the result of the fact that most funds in our sample have a normal return distribution. Therefore, the conditions are not present for the UPR to yield different results. Apparently, managers do not uses options or exhibit market timing skills on a scale that can be detected by analyzing the return distribution. However, we cannot guarantee that managers using options or having superior market timing skills may still show up. A useful application of the UPR may be in the research of hedge funds. Hedge funds are used to leverage the forecasting skills of managers, and they also make use of options and other derivative instrument.

Although the rankings appear similar based on the rank correlation coefficient, we analyzed the differences and find that these differences can be considerable in the case of individual fund managers. Individual managers may very well be ranked 50 places lower than they should be. We analyzed the causes of the differences and we concluded that the skewness again is a significant determinant. Therefore, we prefer to use the UPR as an alternative to the Sharpe ratio, as it gives a more adequate evaluation of the use of options and forecasting skills.

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