**How to assess a manager recovery skill?**

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**Abstract**

*This paper presents a measure that reflects the skill of a manager to recover from a drawdown period. We show that it tends to provide similar results in terms of fund to traditional risk measures for passive strategies but brings additional insights for active investment strategies.*

**Keywords**: Drawdown; Recovery; Manager Skills; Risk Measure

**JEL**: G11, G32

Before the financial crisis, several authors had observed that investors of the mutual fund industry, when choosing among funds, responded to returns ignoring differences in risk (Harless and Peterson [1998]; Berkowitz and Kotowitz [2000]). Yet, the latest financial crisis has left investors wary of risk, and has worsened their confidence in the professionals of the funds industry.

Traditional risk measures such as the variance, the value-at-risk or the maximum drawdown provides the investors with tools to better assess the type of risk they are facing. Regarding their lack of confidence in the specialists, some measures have been developed, in the mutual fund industry, to measure the skills of managers. Unfortunately, these measures generally refer to two types of skills: selectivity (Sharpe [1963], Fama [1972], Grinblatt and Titman [1989] or Stuzer [2000] among others) and market timing (Treynor and Mazuy [1966], Henrikson and Merton [1981] or Weigel [1991]) or both (Brinson, Hood and Beebower [1986]). These measures tend to concentrate on the performance and do not really integrate an assessment of the manager’s ability to cover against risk.

This paper proposes a new measure that tries to complement the study of these skills by analyzing the skill of a manager to recover from a loss. Indeed, we assess the relative responsiveness of the fund performance after a period of steady decrease in value. The relative speed in case of recovery with respect to other comparable mutual funds is linked to the ability of the manager to appropriately rebalance the fund.

The interest of assessing the recovery capacity of a manager may interest both investors and management companies. The financial literature generally focuses on the resilience of managers to shocks, what is generally called stress-testing, but often ignores the post stress period. Based on this observation, we propose to analyze the time necessary to recover from a given drawdown compared to the time from the initial peak until the end of the drawdown period. In other words, this measure provides a first view on a manager time to recovery adjusted to the magnitude of the considered drawdown.

Many papers study the impact of a drawdown constraint on the optimal portfolio characteristics (see for instance Alexander and Baptista [2006]) or the role of the maximum drawdown as the risk measure to minimize (see for instance Hamelink and Hoesli [2003] or Chekhlov, Uryasev and Zabarankin [2005]). However, no paper takes together the notions of drawdowns and time to recovery.

**Description of the recovery measure**

As already mentioned, we propose to build the risk measure on the basis of the drawdowns and the time to recovery corresponding to each drawdown for a given price historical time series. We define it as:



Where is the number of drawdowns identified over the period under analysis, the period of time between the drawdown date (the lowest value of the sub-period) and the time of recovery of the drawdown, the time between the initial peak date and the recovery date related to the drawdown (hence is the proportion of time to recover over the entire period of drawdown) and the magnitude of the drawdown (expressed in percentages).



In Exhibit 1, we show an example of the methodology used to determine the number of drawdowns as well as their magnitude used in the computation of the risk measure.

While the intuition behind the positive impact of the number of drawdowns as well as their magnitude on the measure of risk, we illustrate graphically the impact of the proportion of time up in the total drawdown time in Exhibit 2.

Exhibit 1: Drawdown computation methodology



Both assets in Exhibit 2 share the same number of drawdowns as well as its magnitude. However, these two assets differ in the way they respond to the steady decrease of their values. Indeed, for a given drawdown and time to recovery, Asset A takes relatively much time to go back from its lowest value to its initial value. As a consequence, ceteris paribus, this might indicate a lower manager’s ability to actively reallocate his assets. Tis would result in a higher risk measure for asset A than for Asset B.

Exhibit 2: Two assets with the same number of drawdown and drawdown value



Under this approach, we assess the risk from three perspectives combined in a single risk measure. First, it is sensitive to the number of drawdowns that the asset experiences over the period of analysis through the coefficient . This coefficient varies from one asset to the other. The number of drawdowns is intrinsically linked to the volatility of the asset returns. A more volatile asset will exhibit a larger number of drawdowns. As a consequence, a higher number of drawdowns results in a higher risk level (if the volatility is an appropriate measure of risk) ceteris paribus. In addition, the measure integrates the proportion of time to recovery. The latter represents the ascending period during which the asset recovers the maximum loss over the drawdown period and reaches its initial level. A lower proportion is preferable since it implies a faster recovery. In other words, we assume that an investor will always prefer to reach a valley (a drawdown) slowly and recover the initial value of the investment quickly.



This proportion is weighted by the amplitude of the maximum loss incurred during the drawdown period. For example, fund A has only one drawdown in its historical time series and, for this drawdown of -10%, the “time-to-recovery” ratio is equal to 0.5. This leads to a value of -5% for the proposed risk measure. Now, suppose that fund B has a ratio equal to 0.25 and a drawdown of -20%. This will also give a risk measure of -5%. In fact, an investor will be indifferent between both funds. Therefore, higher is the drawdown, quicker must be the time-to-recovery. This is a strong assumption that we use for the rest of this paper.

The main improvements of this risk measure are twofold. First, we propose a single measure integrating features from both standard deviation and drawdown analysis. Second, it provides additional information on the speed at which a fund manager is able to get back from incurred losses. As a result, our measure not only assesses risk from a negative return perspective but also takes into account the risk linked to the manager’s ability to efficiently rebalance the fund after a period of steady decrease.

**Passive strategy ranking analysis**

We test the effectiveness of the proposed risk measure on 27 indexes representing various asset classes and geographical exposures. We classify them according to their risk measured by our approach as well as using seven commonly used measures of risk i.e. the standard deviation, the (excess) modified value-at-risk[[5]](#footnote-5) introduced by Favre and Galeano [2002], the traditional maximum drawdown, the minimum return, the historical value-at-risk, the percentage of negative returns and the semi-deviation[[6]](#footnote-6). This may give us a first indication about the relevance of our new measure in terms of risk estimation. Indeed, the intuition is that, for instance, equity indices should in general be riskier than fixed income indexes or that emerging markets might display additional risk with respect to developed economies.

We use daily returns between April 2001 and April 2010 (2,343 observations).

Exhibit 3: Index rankings 

We report the ranking of our set of 27 indices in Exhibit 3. As we can see, equity indices appear at the top of the ranking in terms of risk while bond indices are concentrated at the bottom of the table. The same trend appears with respect to developed versus emerging market where the latter are in general assigned a higher level of risk. The rankings using our measure also display high levels of correlations with the seven alternative measures except for the percentage of negative returns (see Exhibit 4).[[7]](#footnote-7) This shows that when the expected difference in terms of risk between assets (in this case, indices) is relatively clear-cut, our proposed measure tends to agree with rankings based on alternative risk measures.

Exhibit 4: Kendall correlations between index rankings



Notes: \*\*\*, \*\* and \* respectively mean significant at the 1, 5 and 10% level.

Using the ranking of 27 different investment strategies, we can observe that, in a first approximation, the proposed risk measure is consistent with what financial intuition may suggest as well as with the ranking of the seven alternative measures of risk that we have selected.

The purpose of the following section is to extend this analysis to a larger set of mutual funds for which risk differentiation may be more complex and for which the active asset selection skills of managers are a part of the risk related to the fund.

**Active ranking analysis**

We also compare our measure to the same seven alternative measures of risk using a broad mutual fund database. We compare these different measures according to the correlation between their rankings over 4,136 mutual funds. These mutual funds are collected from DataStream and correspond to all mutual funds in US dollars with a complete history of daily returns between January 2000 and March 2010 (2,651 returns). A pertinent measure of risk is expected to display positive and significant correlations[[8]](#footnote-8) with most (all) of the other risk measures. Especially, the proposed measure should not give results which contradict risk assessment from other common and well established risk measures. On the other hand, too high (quasi-perfect) correlation would imply that the risk measure does not bring any additional information regarding the set of other available risk measures. In this case, the less complicated to implement measure may be preferred.

In this section, we compare the ranking of all the risk measures we have selected with each others. We compute the risk measures for the 4,136 mutual funds in our data set over the entire period (January 2000 to March 2010). We then rank the mutual funds according to their level of risk for each risk measure (the most risky asset is ranked first). Then, we compare the rankings obtained from the different risk measures using Kendall correlation (which is more appropriate for ranking correlations). This allows us to see whether these different measures provide similar information in terms of rankings of assets with respect to their risk. High positive correlations between risk measures rankings would imply that the analyzed measures provide very similar results. On the other hand, risk measures exhibiting negative correlations may be considered as contradictory. As we can see from Exhibit 5, some risk measures display high levels of Kendall correlations such as standard deviation with both historical Value-at-Risk and semi-deviation, minimum return with both Modified Value-at-Risk and semi-deviation or the semi-deviation and the historical Value-at-Risk.

Exhibit 5: Kendall correlations between risk measure rankings



Notes: All correlations are significant at the 1% confidence level.

Focusing on the correlation of our measure of risk, we can first notice that it does not show negative correlation with any of the other measures of risk. Since we selected these measures of risk as being the most traditional and commonly used measure of risk by both practitioners and academics, we can conclude from this analysis that our measure does not conflict with what are accepted as appropriate measures of risk. On the other hand, while the correlations of our measure with the other risk measures are never negative, they are nonetheless never too close to one. As explained above, a too high correlation would imply that one of the analyzed measures does not really bring any new information with respect to the other. As a consequence, the measure which is either the easiest to compute or simply the most commonly used in practice might be seen as the best alternative while the other might be disregarded as being redundant. In this context, our new measure is supported by the results regarding the correlation with other common risk measures. On the one hand it has a positive Pearson and Kendall correlation with all the other measures while these correlations are not too close to one. Indeed, our measure brings additional information in terms of risk rankings notably by integrating in a single value the features of several other measures. Especially, our measure includes return standard deviation through the number of drawdowns, the magnitude of the drawdowns and the speed at which a manager is able to get back the incurred loss.

**Conclusion**

In this paper, we introduced a new measure of risk integrating three features of fund risk. In addition to volatility and drawdown magnitude, it also reflects risk from the perspective of a manager’s ability to react to a period of negative returns through the speed at which an incurred loss is recovered. We showed that it tends to provide a similar ranking of strategy indices (for which the difference in risk is relatively obvious) to other commonly used risk measures. This demonstrates the consistency of the proposed risk measure. On the other hand, when applied to a large set of actively managed mutual funds, it tends to provide risk ranking somewhat different from the alternative risk measures. Indeed, since our measure integrates a risk dimension related to manager skills, it is not surprising to see that ranking from our measure differ from those measures not taking this feature into account when applied to actively managed mutual funds instead of passive strategy indices. This tends to support the idea that our measure of risk does effectively bring some additional information with respect to the set of traditionally used risk measures.[[9]](#footnote-9)

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5. The (excess) Modified Value-at-Risk is measured as :

   

   Where

   

   And is the standard deviation of returns, S the skewness, K the excess kurtosis and the quantile of a standard normal distribution. We use the 97.5% MVaR throughout this paper.

   

   [↑](#footnote-ref-5)
6. The semi-deviation is defined here as the standard deviation of negative returns. [↑](#footnote-ref-6)
7. The ranking based on the percentage of negative returns as measure of risk display relatively low levels of correlations with all of the other measures of risk used in this paper. [↑](#footnote-ref-7)
8. Kendall’s correlation [1938] is a non-parametric statistic specially designed to compute the degree of correspondence between two ordinal series, like rankings. [↑](#footnote-ref-8)
9. We can notice that the percentage of negative returns also tends to provide relatively low mutual fund ranking correlation with all the other risk measures. However, contrary to our measure, these correlation coefficients are also relatively low for passive strategy index rankings. [↑](#footnote-ref-9)