RISK-AI
RISK MANAGEMENT for ALTERNATIVE INVESTMENTS

Hedge Fund Risk Analysis Guide

This document describes the methodologies used by Risk-AI, LLC in analyzing Hedge Fund Risk

14 Wall Street, 20th Floor, Suite 2060
New York, NY 10005 | contact@risk-ai.com

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Introduction

We are pleased to publish this guide for the use by fund of hedge fund managers, research analysts, other alternative investments professionals and students.

The guide provides an overview of the process used by Risk-AI's professionals in performing advisory functions to our clients. The examples shown in this document represent the tools provided by Transparency Analytics® software.

This document provides guidance to performing analysis based on historical information provided by hedge funds either directly to investors, or through one of the hedge fund database.

The document does not address analysis of position or exposure information that can often be obtained from hedge fund managers.

For any questions regarding information discussed in this document, please send an email to contact@risk-ai.com .

Hedge Fund Analysis Overview

Quantitative analysis based on historical returns may provide useful information about hedge fund risk and return characteristics. In addition, such analysis can help explain hedge fund performance in terms of exposure to different risk factors and changing market environments. The analysis can be used to estimate or forecast hedge fund performance during different scenarios and market conditions.

We should warn our readers that no statistical analysis can provide full explanation of hedge fund performance and risk, and should not be used as the only tool in making any investment decision. Rather such analysis should be used in conjunctions with qualitative review, due diligence efforts and analysis of available transparency.

Generally speaking, the quality or statistical significance of any analysis increases with increasing the lengths of the historical track record. While it's technically possible to perform most analysis on the funds with as few as six monthly returns, we do not recommend assigning such analysis a lot of statistical significance.

Basic Statistical Analysis

Analysis of hedge fund risk and return profile starts with reviewing basic statistical properties of the fund's performance track record. While there are many different statistics that can be calculated for any given fund we focus on the following few statistics.

Annualized Return

Average monthly returns expressed in annualized terms. The monthly return is transformed into annual using continuous compounding

Equation 1

$$R_{annualized} = (1 + \overline{R_m})^{12} - 1$$

Annualized Volatility

Standard deviation of monthly return annualized using the following formula:

Equation 2

$$V_{annualized} = V_{monthly} * \sqrt{12}$$

Skew

Represents asymmetry of the distribution of monthly returns.

Kurtosis

Represents peakedness of the return distribution. High level of kurtosis generally suggests a presence of "fat tails" in the return distribution. Normal distribution has a kurtosis of 3.0.

Serial Correlation (AC1)

Serial Correlation (aka auto correlation) shows the correlation of the of current month return to previous month's return. Serial correlation can often be a measure of relative illiquidity of the fund. Strategies with highly liquid instruments (e.g. equities and futures) tend to have very low serial correlation. Strategies with more illiquid instruments (e.g. Distressed), or strategies where large part of performance comes from repetitive cash flows (e.g. coupon payments in Fixed Income Arbitrage) would tend to have higher level of serial correlation.

Maximum Drawdown

Represents the maximum drawdown (distance from peak to trough) over the fund's history. The drawdown number is useful in estimate the overall downside potential of the fund. Examination of historical drawdowns also provides

Value at Risk (VaR)

Value at Risk represents a minimum amount that an investor may expect to lose due to volatility of the fund given a certain confidence interval. There are multiple ways of calculating VaR:

1. *Parametric*

2. *Historical*
3. *Monte Carlo*

Parametric VaR relies on the assumption of the underlying return distribution and is the most often criticized number. The criticism comes from the fact that most of the time VaR is calculated using assumptions of normal distribution that does not often apply to hedge funds. Under normal distribution assumption VaR would be calculated using equation 3.

Equation 3

$$VaR_{normal} = \mu - Z\theta$$

Where:
μ *is an average monthly return and* θ *is standard deviation of monthly returns.*

Z represents the Z-score or the appropriate confidence interval. For a 95% confidence interval the Z-Score is about 1.65. One way to deal with the normal distribution assumption is to use Cornish-Fisher adjustment that incorporates skew and kurtosis of distribution and changes the Z-Score used in equation 3. The Cornish-Fisher adjustments are shown in Equation 4.

Equation 4

$$Z_{cf} = Z + \frac{Z^2 - 1}{6}S + \frac{Z^3 - 3Z}{24}K - \frac{2 * Z^3 - 5Z}{36}S^2$$

Where Z is the Z calculated under normal distribution assumption, S is skew and K is the kurtosis of the distribution.

Historical VaR is a simple calculation of the worst percentile of historical returns of the fund. A 95% confidence level historical VaR of the fund with 100 months of data would be calculated as simple the 5th worst return of the fund. Hedge funds often have short performance histories so historical VaR may not always be appropriate.

Monte Carlo VaR is calculated using simulation of theoretical fund returns based on some underlying model. See Monte Carlo section below.

Within Transparency Analytics® platform we currently calculate parametric VaR (both normal and adjusted using Cornish Fisher formula). We do not, however, attribute significant importance to any VaR calculations.

Sharpe Ratio

Sharpe Ratio is perhaps the most overused tool in the analysis of hedge funds. Sharpe Ratio is calculated using equation 5.

Equation 5

$$Sharpe = \frac{R - Rf}{V_{R-Rf}}$$

Where R is the average return of the fund, Rf is return of the Risk Free instrument (e.g. 1 month Treasury Bill). R-Rf is then the excess return of the fund. V is the volatility of this excess return.

Sortino Ratio and Downside Volatility

Hedge Fund managers and investment analysts often quote Sortino Ratio as an important statistic. Sortino ratio changes the denominator in Equation 5 to be the volatility of the downside or (negative returns).

We do not recommend using Sortino Ratio (and do not currently provide it within Transparency Analytics). Hedge funds in general have relatively short histories. Based on our previous studies, the average life span of a hedge fund is about 66 months. About 27% of existing hedge funds have less than 3 years of history. This means that for many hedge funds, separating data into subsets of positive and negative performance significantly reduces statistical significance of any calculations.

*We also find that Sortino Ratio is often used or advertised by the funds that have high volatility, but have not **yet** suffered significant losses. We believe that in such cases the fund manager needs to demonstrate qualitative evidence of why his or hers strategy has high Sortino ratio.*

Rolling Analysis

The basic analysis described above is useful to evaluate risk / return profile of the fund over the complete history. It may often be useful to evaluate changes in certain statistics over time. Simple time series line plots are often used to examine the changes in the data (Figure 1).

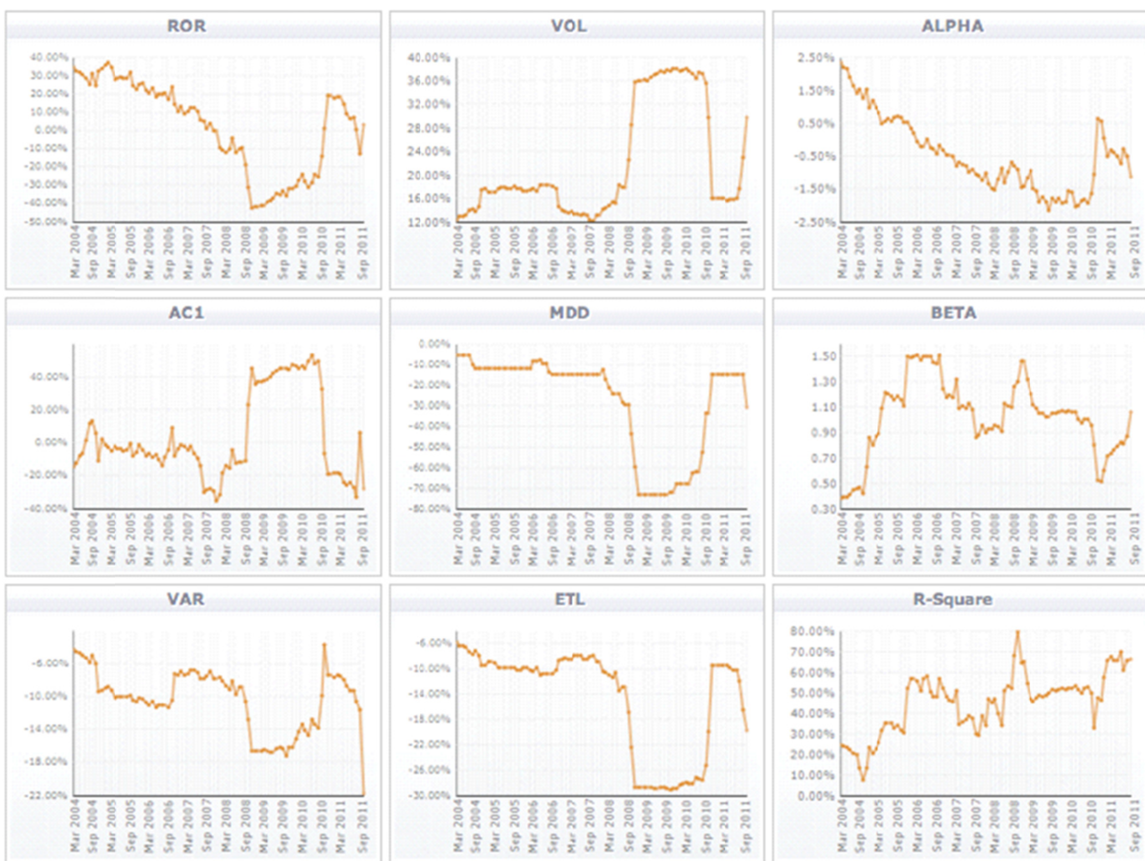


Figure 1

The advantage of rolling chart is that they allow investors to examine changes in some of the important risk statistics. The drawback of such analysis is that rolling statistics reduce the size of the analyzed data. In addition, the first N data points are often lost in producing the rolling number. (Here N represents the size of the rolling window). We typically recommend using a rolling window of at least 12 months.

In addition to standard rolling charts we often recommend using Cumulative Squared Return Chart (Figure 2).

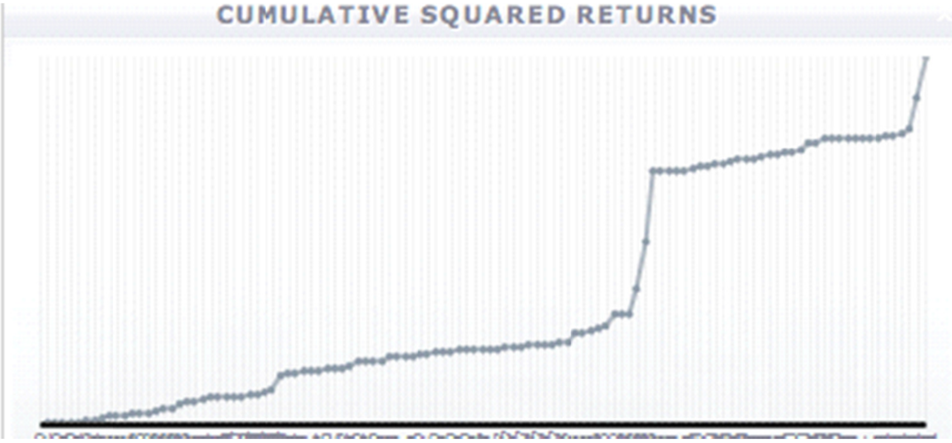


Figure 2

Cumulative Squared Return Chart allows investor to quickly identify changes in volatility on a month by month basis rather than on the rolling 12 month basis. The changes in volatility are identified by the changes in the slope of the blue line in the chart.

Drawdown Analysis

Drawdown Analysis provides information about historical drawdowns experienced by the fund and allows investor to evaluate

1. *The size and length of historical drawdowns*
2. *Typical recovery time for drawdowns.*
3. *Historical context in which drawdowns happen.*

Underwater Curve (Figure 3) is helpful in examining historical drawdowns.

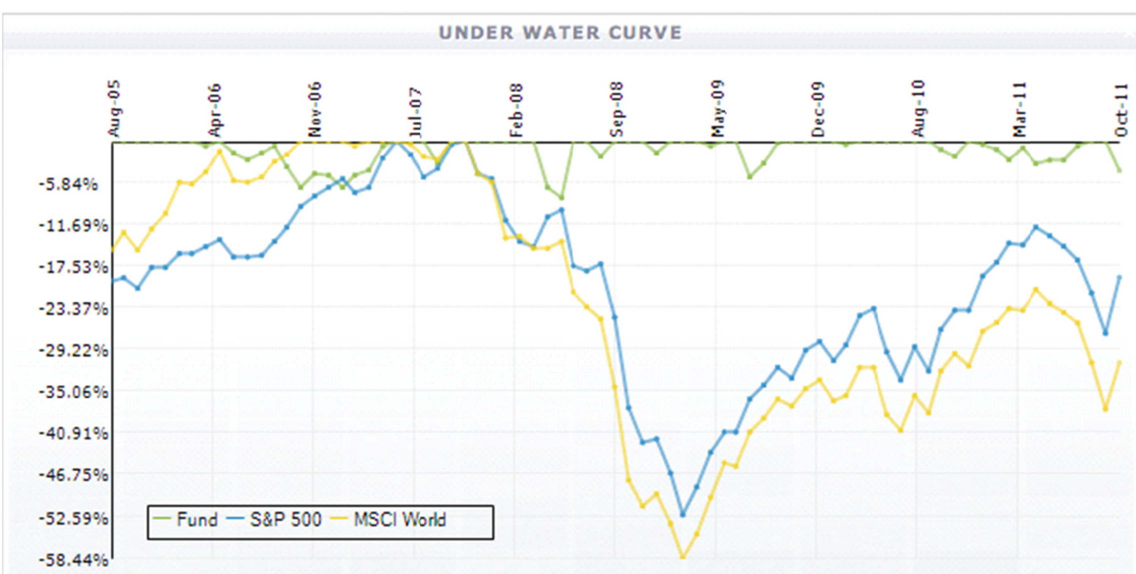


Figure 3

In the example above we can see that the fund's drawdown (green line) has been significantly less severe than those of MSCI World and S&P 500 indexes. We can also see that the drawdown has been significantly shorter in terms of both duration and recovery time.

It's also helpful to display drawdown analysis in tabular format to examine the size, duration and recovery time of each historical drawdown (Figure 4).

Start Date	End Date	Length	DrawDown	Time To Recover	S&P 500
Mar-2006	Mar-2006	1	-0.65%	1	1.11%
May-2006	Jan-2007	9	-6.51%	4	9.74%
Aug-2007	Aug-2007	1	-3.15%	1	1.29%
Apr-2008	May-2008	2	-7.80%	1	5.87%
Aug-2008	Aug-2008	1	-2.16%	1	1.22%
Dec-2008	Dec-2008	1	-1.53%	1	0.78%
Apr-2009	Apr-2009	1	-0.60%	1	9.39%
Jul-2009	Jul-2009	1	-4.95%	3	7.41%
Feb-2010	Feb-2010	1	-0.30%	1	2.85%
Sep-2010	Oct-2010	2	-1.96%	1	12.76%
Dec-2010	Apr-2011	5	-3.08%	4	15.51%
Oct-2011	Oct-2011	1	-4.10%	1	10.77%

Figure 4

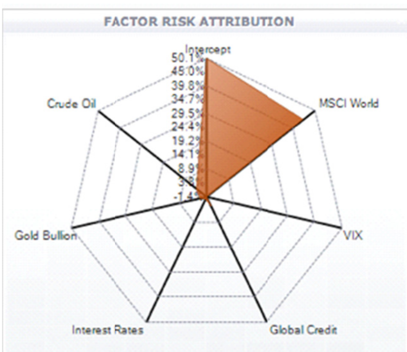
Performance Attribution

Performance attribution is a tool that allows us to put the recent performance of the fund into historical context. One way to do that is to forecast the fund's performance based on some theoretical model and then calculate contribution to performance suggested by the model and compare the produced forecast to actual results.

One way to forecast a fund's theoretical returns is to use a factor model:

1. *Estimate the fund's sensitivity to every risk factor in the model.*
2. *Use the actual performance of the factors during the period and multiply these by the fund's sensitivity to each factory.*
3. *Calculate the total explained P/L and compare to actual.*

Figure 5 shows sample output for such performance attribution. See Style Analysis section for more on factor models.



PERFORMANCE ATTRIBUTION

ACTUAL P/L	10.63%	EXPLAINED P/L	9.94%	UNEXPLAINED P/L	0.69%

Factor	Beta	PVal	MTD	PL
MSCI World	0.75	0.00	10.62%	7.99%
VIX	0.01	0.70	-30.26%	-0.27%
Global Credit	0.08	0.58	6.78%	0.56%
Interest Rates	-0.01	0.54	NaN	0.00%
Gold Bullion	0.09	0.21	6.59%	0.58%
Crude Oil	0.06	0.07	17.19%	1.08%

TOTAL EXPLAINED P/L 9.94%

Figure 5

The "spider web" chart on the left shows that MSCI World (global equities) is the main risk factor driving performance of the fund. The table on the right shows that based on the performance of the six main risk factors and the fund's sensitivity to these the fund should have produced a return of 9.94%. The fund's actual performance in the month was 10.63% leaving only 69 basis points of performance unexplained.

Another part of performance attribution is analysis of the fund's recent performance with respect to its previous history. This can be accomplished by examining information in Figure 6. In this chart, each series represents distribution of the fund's return over specific period or set of periods. The first box (Orange) shows the distribution of the fund's return over the entire history. The top and bottom lines in the chart show the maximum and minimum monthly returns respectively. The color box shows a range of one standard deviation around the mean of the distribution. The line just above 10% mark shows the performance n the last month. The other three series show the same data but broken down into three market regimes:

Treading Water, Flight to Quality and Bull Market (See Market Regime Analysis below).


FUND PERFORMANCE IN HISTORICAL CONTEXT
Overall
Flight to Quality
Bull Market
Treading Water
25.00%
20.00%
15.00%
10.00%
5.00%
0.00%
-5.00%
-10.00%
-15.00%
-20.00%

Figure 6

Peer Analysis

Peer Analysis is a useful tool for analyzing hedge fund within the context of its stated strategy. Peer Analysis consists of two steps.

1. *Peer Group Identification*
2. *Peer Comparison.*

Peer Group Identification is probably the most difficult part of the analysis. Hedge Fund universe contains anywhere between 6,000 and 12,000 funds depending on the database source. Identification of the proper peer group is therefore critical in order to perform meaningful analysis. There are several methods for constructing peer groups.

1. *Qualitative – In many cases research analysts can construct a peer group of funds based on their qualitative knowledge of the universe and individual funds. Obviously such approach is highly subjective and is subject to limited peer group selection that can be constructed to benefit research analyst's analysis.*
2. *Broad Strategy Classification – This is the simplest and most naïve approach. It suffers from two issues. First. The selection may be too broad and may include funds that pursue very different strategies within the same broad category. Second. The analysis relies on assumption that all funds (including the one being analyzed) are classified correctly.*
3. *Correlation Analysis – Correlation analysis may be a good tool to narrow down the universe of funds selected using second approach. In this case we can perform somewhat objective selection and chose the funds that have the highest correlation to our fund. The analysis stills suffers from self-classification problem. In addition the analysis may suffer from spurious correlation problem. It's theoretically possible for two funds to be highly correlated while pursuing completely different strategies.*
4. *Cluster Analysis – A technique called cluster analysis can be used to place funds into various distinct clusters. The technique may provide the most objective way to separate funds into peer group but as all approaches have some potential issues. First. The analysis is data intensive and will generally require funds with longer track records. Second. The clusters are based on purely statistical properties. This means that the analysis can group funds from very different strategies. This makes cluster identification and interpretation difficult.*

In Transparency Analytics we currently use the approach number 3 to identify peer groups.

Once the peer groups are identified the funds can be analyzed with respect to their selected peers. Ultimately many different tools can be used to compare funds to each other. Within Transparency Analytics® platform we currently provide three types of comparison.

1. *Basic statistical analysis. Once the system selects ten closest peers the analysis compares properties of distribution of returns of all peer funds as shown in Figure 7.*

MOST CORRELATED PEERS

NAME	ANN ROR	ANN VOL	MAX DD	CORRELATION	UP CORR	DN CORR	RANK CORR
Fund 64578	50.89%	30.66%	-30.13%	100.00%	100.00%	100.00%	100.00%
Fund 75121	3.83%	7.12%	-8.18%	59.81%	61.69%	46.26%	58.08%
Fund 77438	21.32%	9.57%	-3.59%	39.86%	52.39%	14.38%	42.66%
Fund 75293	18.62%	5.66%	-1.06%	39.40%	37.06%	39.06%	42.67%
Fund 76866	2.88%	3.96%	-5.11%	37.39%	32.81%	22.85%	31.02%
Fund 75160	13.84%	8.12%	-8.91%	36.65%	38.83%	44.62%	19.77%
Fund 74480	4.14%	6.63%	-8.82%	35.77%	39.76%	40.90%	31.43%
Fund 76652	13.24%	5.71%	-3.16%	34.03%	40.19%	11.59%	25.30%
Fund 73619	8.52%	5.96%	-6.46%	33.57%	49.05%	49.05%	34.23%
Fund 73788	-0.56%	5.39%	-8.06%	33.41%	42.35%	41.52%	29.78%
Fund 76809	20.51%	13.08%	-11.81%	32.10%	31.58%	27.97%	37.14%

Figure 7

The analysis provides a quick comparison of statistical properties and correlations for fund being analyzed and the ten closes peers. This analysis is performed over the overlapping track record. We can also compare entire return distributions of all funds using chart shown in Figure 8.

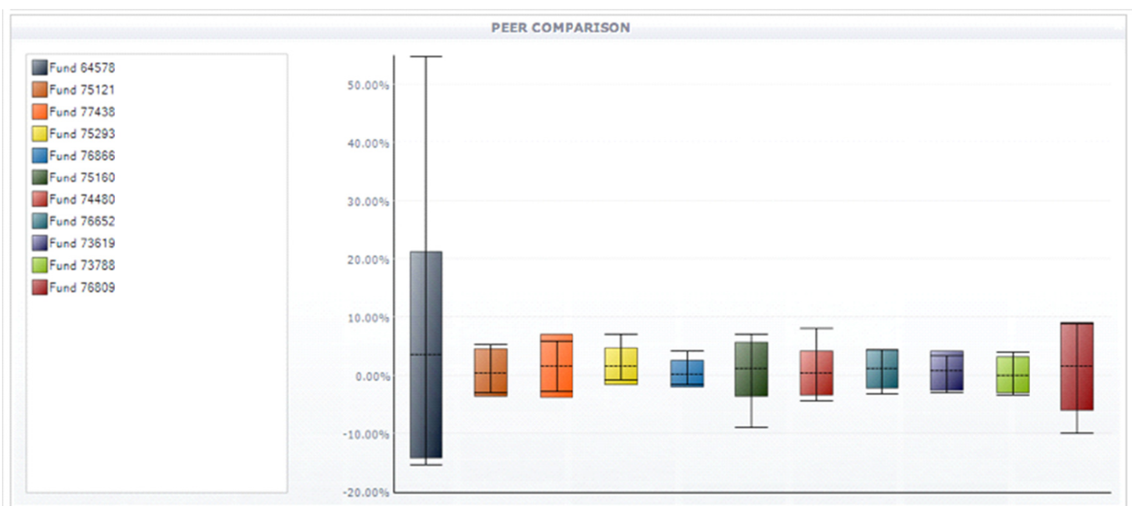


Figure 8

In this chart the middle line shows average monthly return of all funds. The color boxes show one standard deviation range around the average. The top and bottom bars show the maximum and minimum returns for each fund. The chart allows us to quickly compare the return and volatility profiles of all funds.

2. *Correlation, Leverage and Return Comparison*

It may also be useful to look at the fund comparison not only in terms of correlation and returns but to incorporate relative leverage as well. In absence of position and comparable exposure data relative leverage may be estimated as the fund's Beta to the appropriate benchmark strategy or peer group. All hedge fund betas may then be standardized (to have mean 0 and standard deviation of 1.0) and z-scores calculated. The funds with high Z scores will then have relatively high leverage while the funds with low Z-scores will have relatively low leverage. When looking at large universe of funds the chart shown in Figure 9 may be helpful.

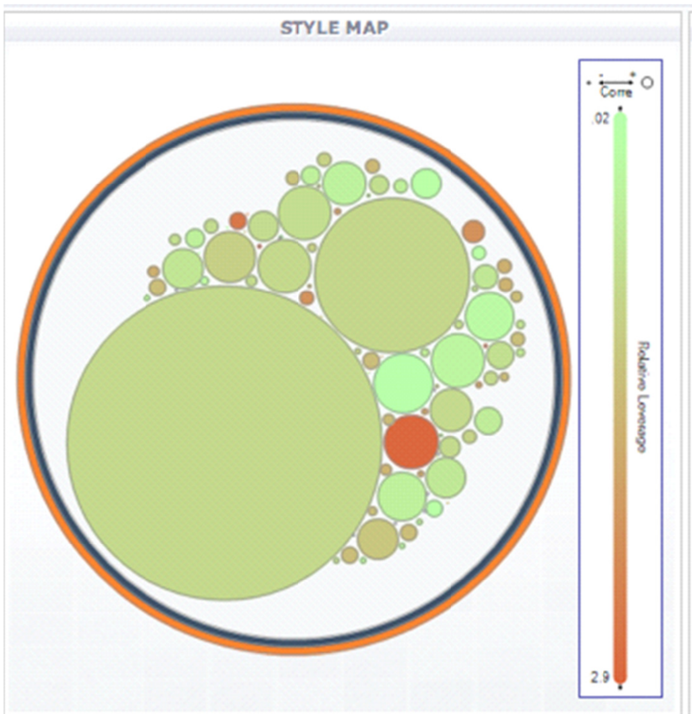


Figure 9

In this chart the size of each circle represents the correlation of the peer to our fund. The largest circle is the fund itself. The color of each circle represents the relative leverage. The chart gives us a quick way to identify the most correlated funds as well as most levered funds within the strategy.

A complementary chart allows us to compare the most correlated peers and plot their leverage, return and volatility in one simple chart (Figure 10).

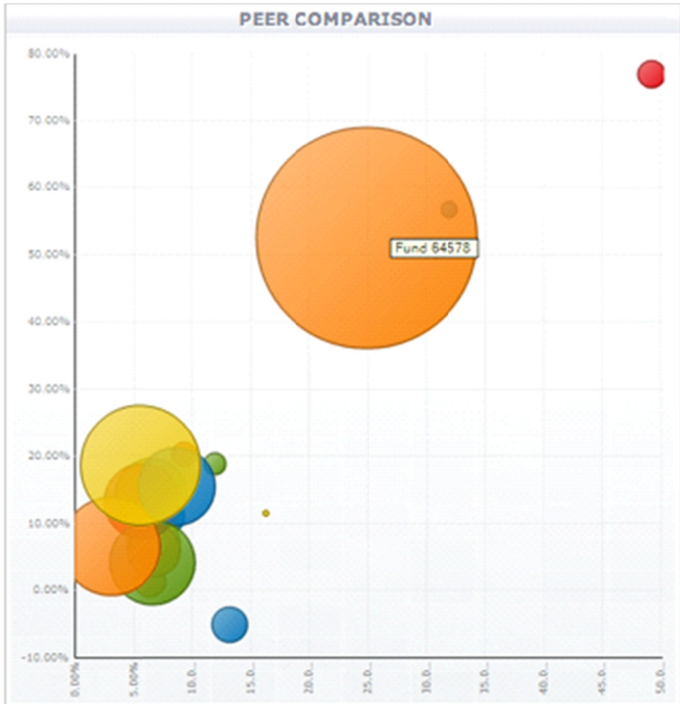


Figure 10

Ultimately, to get a true comparison of the fund, it's important to compare the funds in terms of all relevant statistics and analysis described in this document. Within Transparency Analytics we provide a fund comparison report that allows investors to compare two funds using the following tools.

1. *Basic Statistics*
2. *Return Distribution*
3. *Historical Returns*
4. *Style Analysis*
5. *Non Linear Sensitivity*
6. *Stress Tests*
7. *Tail Risk*
8. *Market Regime Analysis.*

Figures 11, 12 and 13 show the screen shot of sample fund comparison.

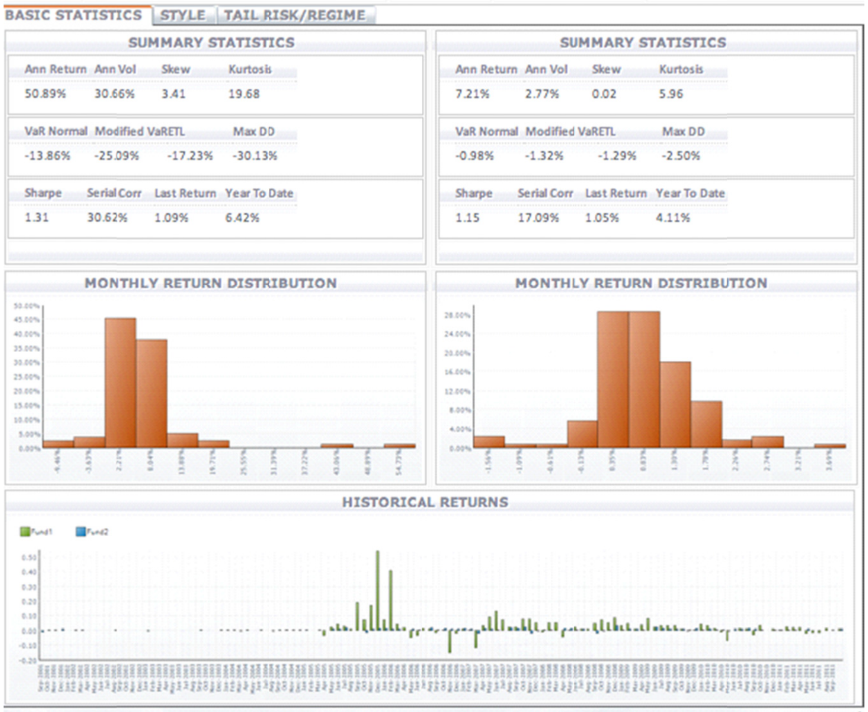


Figure 11

Figure 12


PARALLEL SHIFT - FUND 1
PARALLEL SHIFT - FUND 2
MAXIMUM DRAW DOWN SIMULATION
MAXIMUM DRAW DOWN SIMULATION
REGIME STATISTICS - FUND 1
Regime | Avg Ret | Std Ret | Beta To S&P | # Points
Flight To Quality | 2.84% | 4.37% | 0.02 | 11
Bull Market | 2.44% | 2.72% | -0.20 | 15
Treading Water | 3.97% | 10.52% | -0.08 | 52
REGIME STATISTICS - FUND 2
Regime | Avg Ret | Std Ret | Beta To S&P | # Points
Flight To Quality | -0.12% | 0.60% | 0.04 | 14
Bull Market | 0.84% | 0.79% | -0.04 | 26
Treading Water | 0.62% | 0.76% | 0.05 | 81

Figure 13

Style Analysis

The goal of style analysis is to provide explanation on what risk factors most affect the performance and volatility of the fund. Style analysis is typically performed using linear regression analysis using either single variable or multi variable models.

Correlation Analysis

The simplest way to perform style analysis is to conduct simple correlation analysis with respect to many different risk factors. Such analysis can provide the first look into which factors may be the most relevant. In addition to overall correlation and beta analysis it is often helpful to analyze the correlations during up and down markets for each factor. See Figure 14 for sample correlation report.

Type

Type : Commodity (9)

Name	CORR	UP CORR	DN CORR	Beta	ROR	VOL	MAX DD
Natural Gas	11.94%	11.96%	10.84%	0.01	36.19%	78.74%	-84.78%
S&P GSCI Precious Metals	-7.09%	-7.44%	-10.55%	-0.03	18.08%	18.37%	-30.30%
Crude Oil	9.65%	-4.26%	-3.95%	0.02	16.81%	33.88%	-72.06%
S&P GSCI Agricultural	8.08%	9.21%	8.59%	0.03	1.84%	22.19%	-51.65%
S&P GSCI Industrial Metals	8.47%	-9.81%	-8.76%	0.02	11.62%	23.41%	-61.73%
DJ UBS-Spot Commodity Index	14.14%	5.49%	6.67%	0.05	14.39%	17.90%	-48.94%
Gold Bullion	-11.11%	-9.56%	-13.96%	-0.05	18.52%	16.74%	-21.03%
S&P GSCI Energy	19.68%	11.74%	10.44%	0.04	11.99%	32.88%	-74.57%
Commodities	14.08%	2.82%	3.19%	0.04	13.35%	24.40%	-61.03%

Type : Commodity Future (22)

Type : Credit (29)

Type : Domestic Equity (3)

Name	CORR	UP CORR	DN CORR	Beta	ROR	VOL	MAX DD
S&P 600 SMALL CAP	20.16%	13.85%	12.46%	0.07	8.63%	20.73%	-53.18%
S&P 500	18.40%	8.68%	9.42%	0.08	0.02%	16.42%	-52.56%
S&P 400 MIDCAP	27.49%	23.52%	23.28%	0.10	7.97%	19.05%	-50.95%

Type : Economy (2)

Type : Emerging Market Debt (11)

Name	CORR	UP CORR	DN CORR	Beta	ROR	VOL	MAX DD
BARCLAYS VENEZUELA	12.07%	0.48%	-0.05%	0.05	1.09%	16.89%	-60.65%
BARCLAYS EM AMERICAS CORPORATE	11.70%	5.82%	4.47%	0.08	2.02%	10.43%	-32.24%
BARCLAYS MEXICO	8.40%	10.60%	10.78%	0.02	-6.25%	30.13%	-100.00%
BARCLAYS ECUADOR	11.27%	14.52%	13.97%	0.02	20.33%	43.70%	-75.38%
BARCLAYS ARGENTINA	9.40%	1.18%	2.34%	0.02	4.89%	33.22%	-76.77%
BARCLAYS EM AMERICAS ALL SERIES	11.30%	5.32%	3.37%	0.06	2.71%	12.39%	-33.75%
BARCLAYS PANAMA	5.55%	2.84%	0.46%	0.03	4.36%	10.96%	-28.00%

Figure 14

Multi Factor Regression Analysis

Single factor (aka Univariate) analysis is useful, but does not provide the complete picture of the fund's exposures. We recommend conducting multi-variable regression analysis using different models (combination of factors) depending on the fund's strategy.

Changing from single variable to multi variable format usually allows to explain more of the fund's volatility and to account for interaction of factors. We should note that unless the factors are completely uncorrelated addition of each factor may not increase the explanatory power as much as expected. The diagram in Figure 15 shows the concept of multi variable regression analysis. The two factors have some overlap (correlation) and their explanatory power (overlap with fund) is therefore less than the sum of each individual parts. If, however, the factors were totally independent (correlation of 0) then the sum of explanatory powers would equal to the total explanatory power provided by each factor individually (Figure 16).

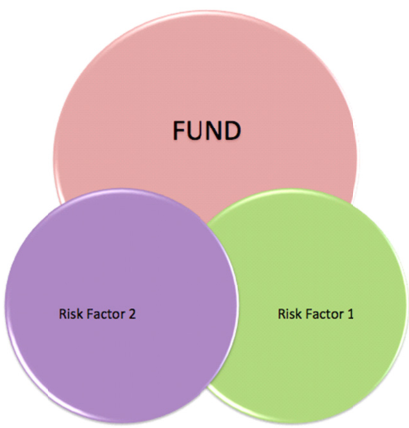


Figure 15

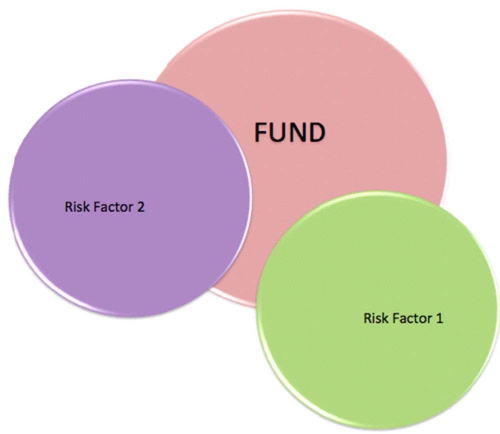


Figure 16

Estimation of multi variable regression is a fairly straightforward task, and can be accomplished using various tools including Microsoft® Excel®. In addition to evaluating the size of exposures (Betas), analysts should look at statistical significance of each factor. Statistical significance is typically determined by examining the value of either t –statistic or p-value. In Transparency Analytics we use p-value to determine if risk factor is statistically significance. Typically we consider factors with p-value less than 0.10 to be statistically significant and factors with p-values between 0.1 and 0.2 to be borderline statistically significant. The results of sample analysis are shown in Figure 17.

MAIN MODEL

Keep	Name	Beta	PVal
☐	Intercept	0.00	0.23
☑	MSCI World	-0.12	0.14
☑	VIX	-0.02	0.19
☑	Global Credit	0.46	0.00
☐	Interest Rates	0.00	0.53
☑	Gold Bullion	0.07	0.11
☐	Crude Oil	0.01	0.77
☐	Adj. R-Square/P(F)	0.60	0.00

Figure 17

The adjusted R-Square statistic shows the explanatory power of the model. The value of 0.60 shown in Figure 17 signifies rather significant explanatory power.

As we can from example in Figure 17 several factors have at least border-line statistical significance. Having estimated the fund's sensitivities to each factor we can now estimate each factor's contribution to the fund's volatility. To do that, we can think of the fund's overall volatility as shown in Equation 6.

Equation 6

$$V = w' \sum w + V_{specific}$$

Where $\mathbf{\Sigma}$ *is the factor covariance matrix and* $\mathbf{w}$ *is the vector of fund's sensitivities (betas) to the risk factors.*

The equation says that the fund's volatility is the function of the covariance of the risk factors and fund specific volatility. This means that each fund's contribution to volatility can be calculated as shown in Equation 7.

Equation 7

$$CRisk = \frac{\mathbf{\Sigma} * \mathbf{w}}{V}$$

Please note that factor contribution to risk may be negative. Factor contribution to risk can be easily visualized in a "spider web chart" in Figure 18.

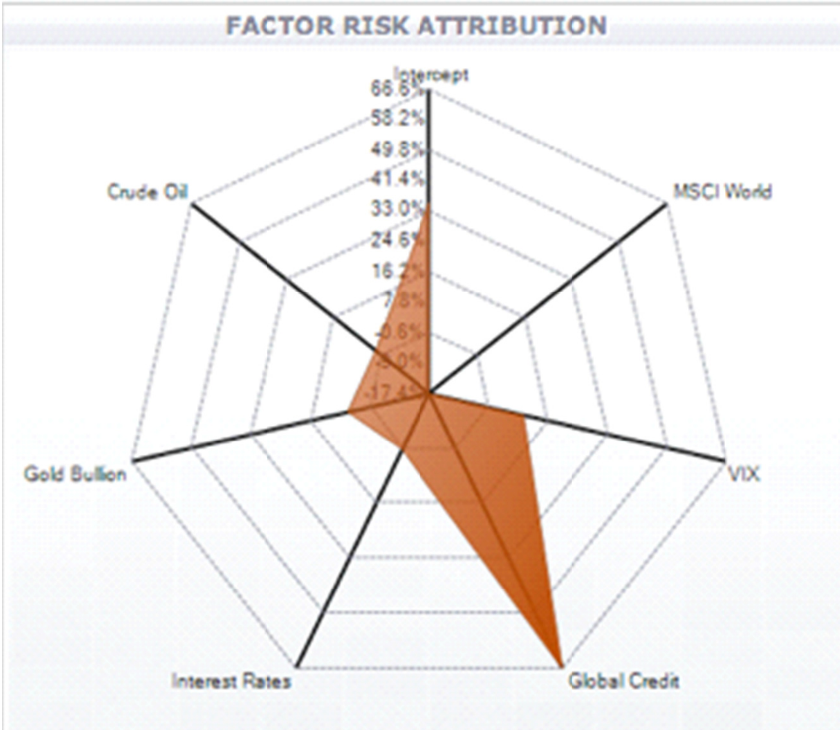


Figure 18

To read the chart you must follow the lines from the Y-Axis to the intersection with the shaded area at each factor. For example the Global Credit contribution to risk is about 66.6%.

In addition to static analysis it is often helpful to perform style analysis and factor attribution on rolling basis as well. The analysis is typically visualized in charts such as shown in figures 19 and 20.

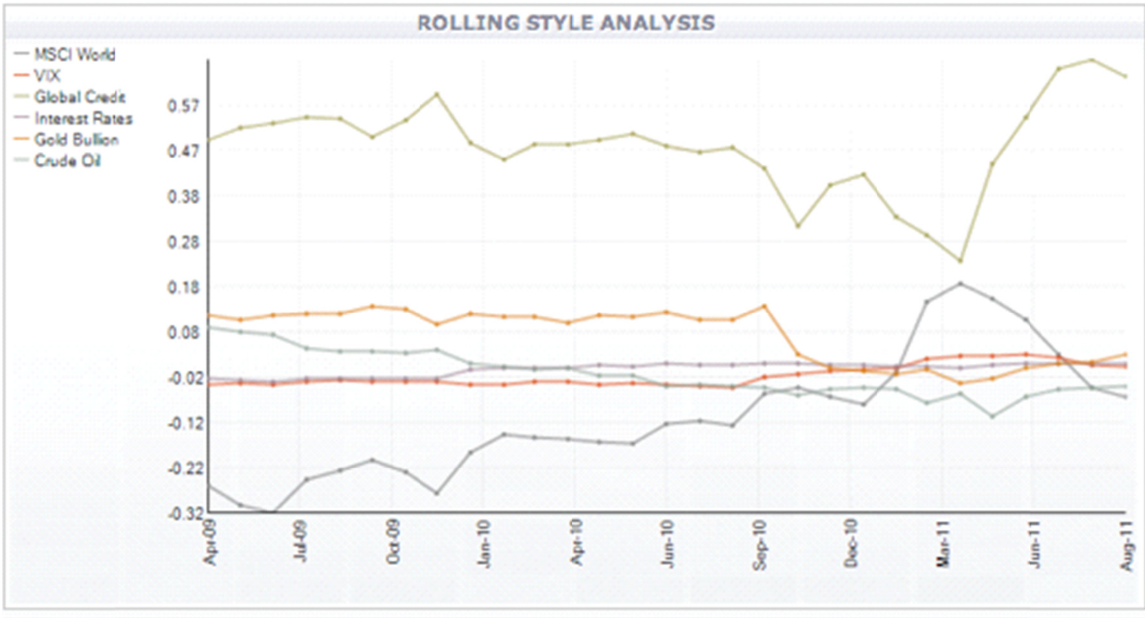


Figure 19

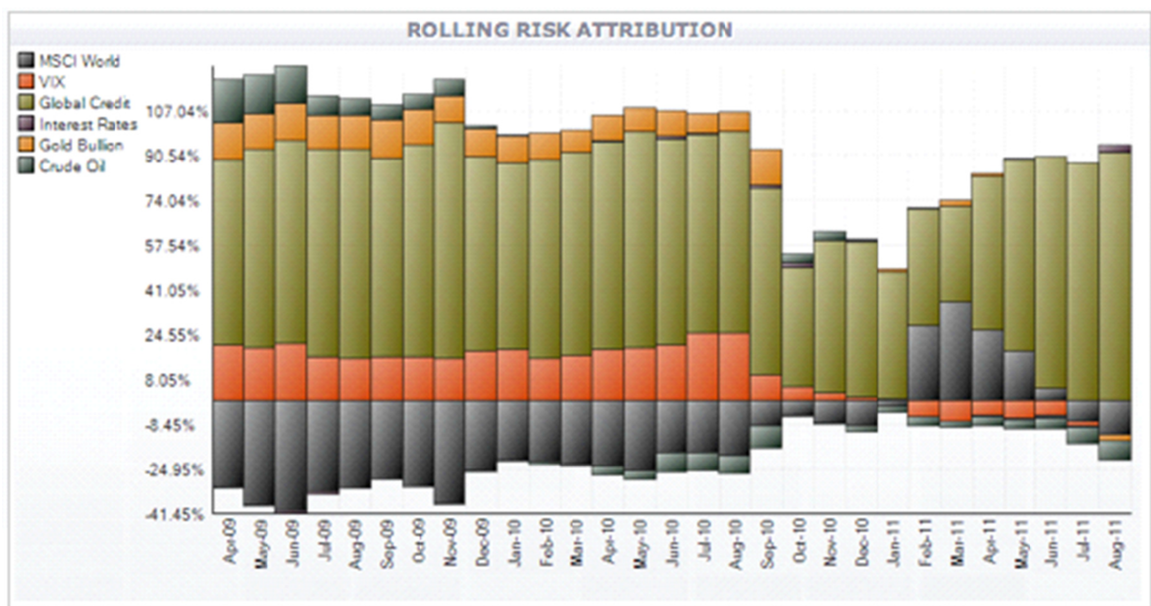


Figure 20

Stepwise Regression Analysis

By default, style analysis within Transparency Analytics® platform start with the use of our main model that contains six factors: Global Equity, Global Credit, Equity Volatility, Interest Rates, Gold and Oil. In addition to the main model analysts can chose from a variety of other models or create their own. It is not, however, always obvious which factors would provide best explanatory power for the fund. In order to help with the selection of the most relevant set of factors investors can run a Stepwise Regression Analysis. Stepwise regression analysis scans a large universe of risk factors and selects the factors that have the most statistical significance and maximize the explanatory power of the model.

Once the factors are identified the rest of the analysis is the same as the one described in the previous section. The sample output for the overall regression statistics is shown in Figure 21.

STEPWISE MODEL

Keep	Name	Beta	PVal
☐	Intercept	0.01	0.02
☑	GIC: Energy	0.05	0.12
☑	BAFCLAY US BBB	0.69	0.00
☐	Adj. R-Square/P(F)	0.58	0.00

Figure 21

When performing regression analysis the selection of factors plays an important role. The factors should have not only statistical significance but also economic significance for the fund's strategy.

Convexity Analysis

Linear regression analysis is a very useful tool and provides investors with information about linear relationships between the fund and the various risk factors. It does, however, have limitations. When used for forecasting the analysis can be generally applied to small movements in the underlying risk factors.

In the absence of position level transparency or exposure information, regression analysis is also often used for scenario and stress test analysis (see below). Unfortunately linear nature of the analysis makes such application inaccurate. To improve accuracy of such analysis we recommend conducting non-linear sensitivity or Convexity analysis.

To be sure the analysis is still based on linear regression but now incorporates a non-linear factor. In the simplest form the analysis adjusts CAPM-style model (Equation 8) by adding a non-linear term (Equation 9).

Equation 8

$$E(R) = \alpha + \beta x + \varepsilon$$

Equation 9

$$E(R) = \alpha + \beta_1 x + \beta_2 x^2$$

The formula is based on the model by Treynor-Mazuy for evaluating the market timing ability of mutual fund managers. The theory is that the manager that does not try to time the market will generate returns along the Security Market Line.

If, on the other hand, the manager is able to time the market then he or she will dial up the exposure before the market goes up and dial down exposure before the market suffer losses. In this case the manager's payoff with respect to the market will have non-linear profile. The difference between the linear and non-linear pay off profiles is demonstrated in Figure 22.

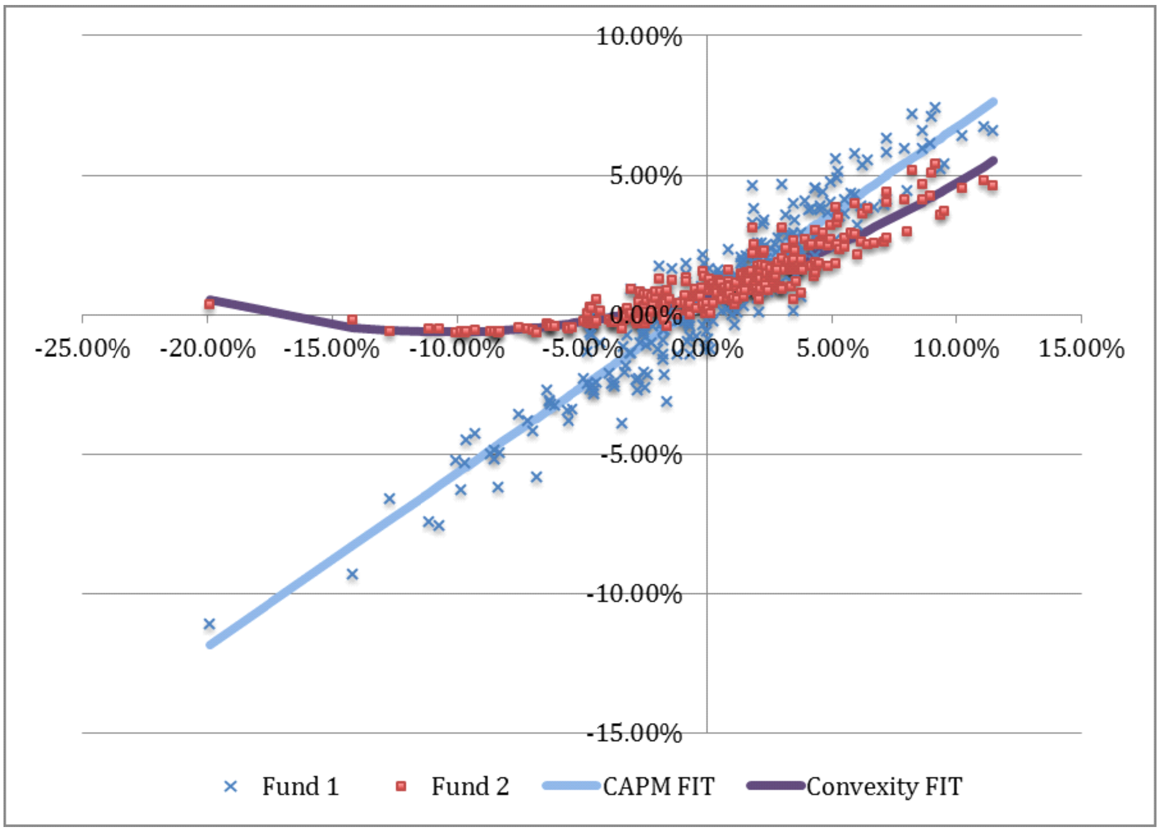


Figure 22

The market timing interpretation works well within Mutual Fund context but does not always apply to evaluating hedge funds. Hedge funds tend to trade in more complex strategies using wider variety of products than do mutual funds. Hedge Fund can, therefore, create this type of non-linear profile without trying to specifically time the market. We, therefore, offer a more general interpretation. The fund's sensitivity to the squared factor can be thought of as fund's convexity with respect to the benchmark risk factor. This type of convexity can be viewed the same way as Gamma in option pricing and Convexity in bond pricing. Its use becomes critical when evaluating changes in response to large movements in the underlying benchmark.

Within Transparency Analytics we provide non-linear sensitivity analysis tools that allows investor to compare the fund with respect to a single factor (Figure 23).

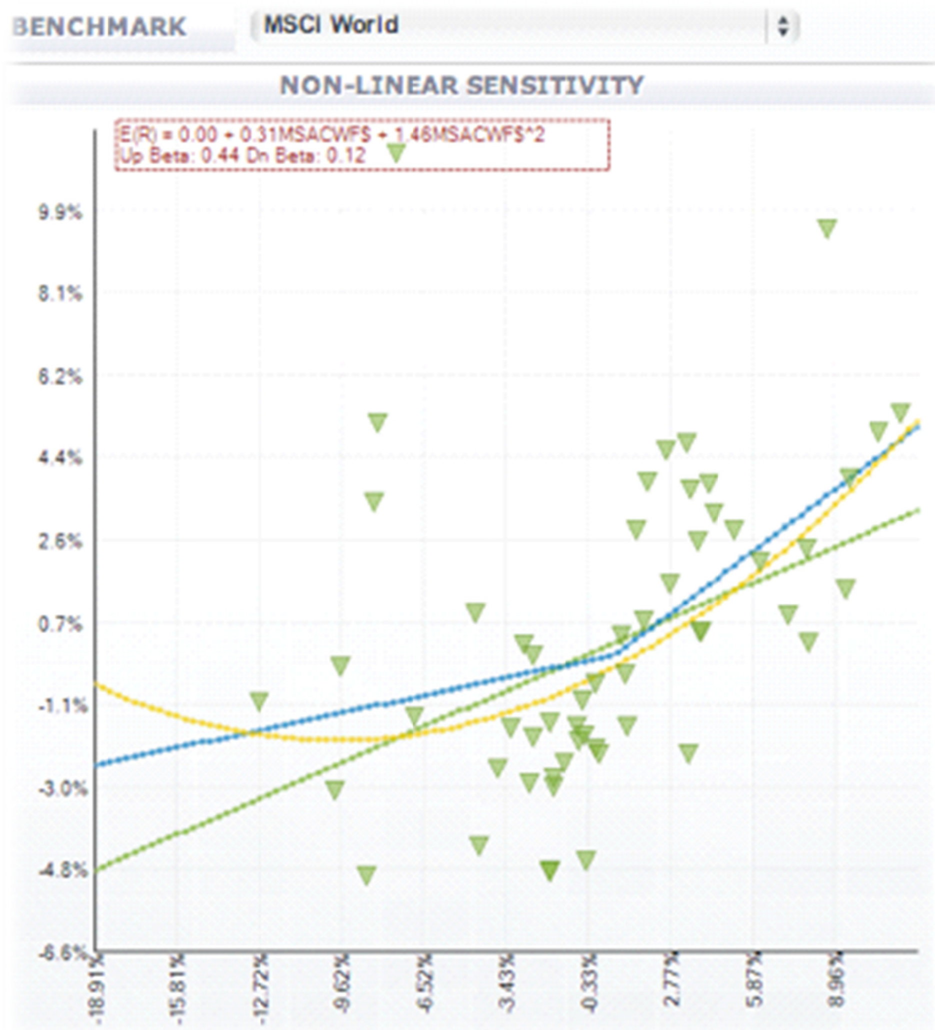


Figure 23

Tail Risk Analysis

Tail Risk Analysis involves evaluation of the fund's performance during either historical or theoretical stress events as well as evaluation of general potential downside that may be experienced by the fund. Several tools can be used to perform such analysis.

Scenario Analysis and Stress Testing

Scenario and Stress Testing involves forecasting of the fund's performance due to certain movements in market factors. Historical Stress Testing typically involves reconstruction of significant historical market events such as Technology Crash in 2002, September 11 attacks, Lehman Brothers bankruptcy and others. Scenario analysis is used to create theoretical stresses (e.g. Equity Down by 20%, Gold down by 10%, etc.).

In the world where position and exposure information is not available style analysis is typically used to forecast fund's response to such events. As discussed above we recommend incorporating non-linear sensitivity to such analysis.

Our approach to stress testing and scenario analysis is described below.

Historical Stress Testing

We perform non-linear style analysis using Equation 9 to evaluate the fund's sensitivities to performance of the fund's overall strategy. We then use the strategy's actual performance during historical stress events to estimate fund's performance.

The approach relies on the assumption that the fund's exposure to the overall strategy remains constant in different market conditions.

The output of historical stress tests is shown in Figure 24.

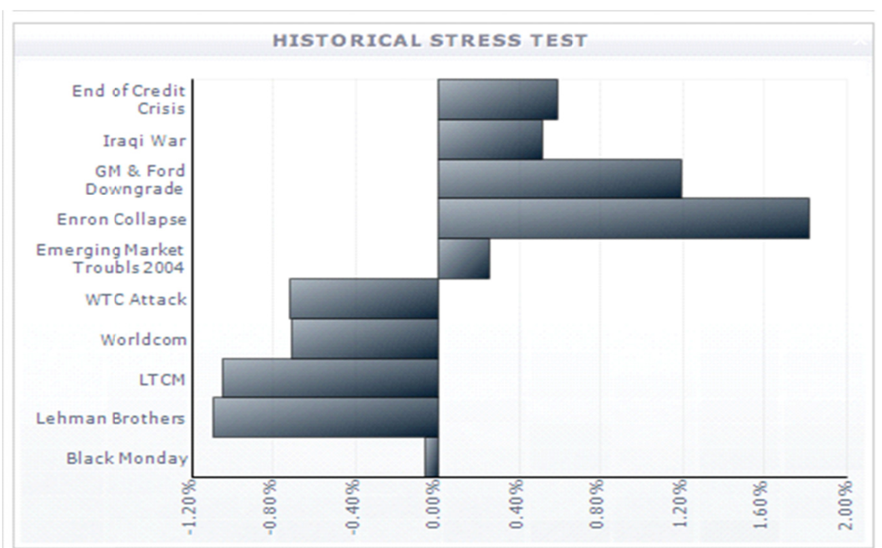


Figure 24

Scenario Analysis

We perform scenario analysis using both single factor and multi factor models. When using multi-factor model we generally turn off the convexity evaluation (do not include squared return factors). The reason for that is the limited number of data points typically available for analysis. When using linear regression it's generally recommended that the number of data points available is at least three to four times larger than the number of factors. Adding squared factors to all "normal" linear factors would double the number of data points required for analysis.

We provide two tools for performing scenario analysis. The first tools provides a simple chart that shows the fund's estimated performance due to 20% up and 20% down movements in six main risk factors (Figure 25).

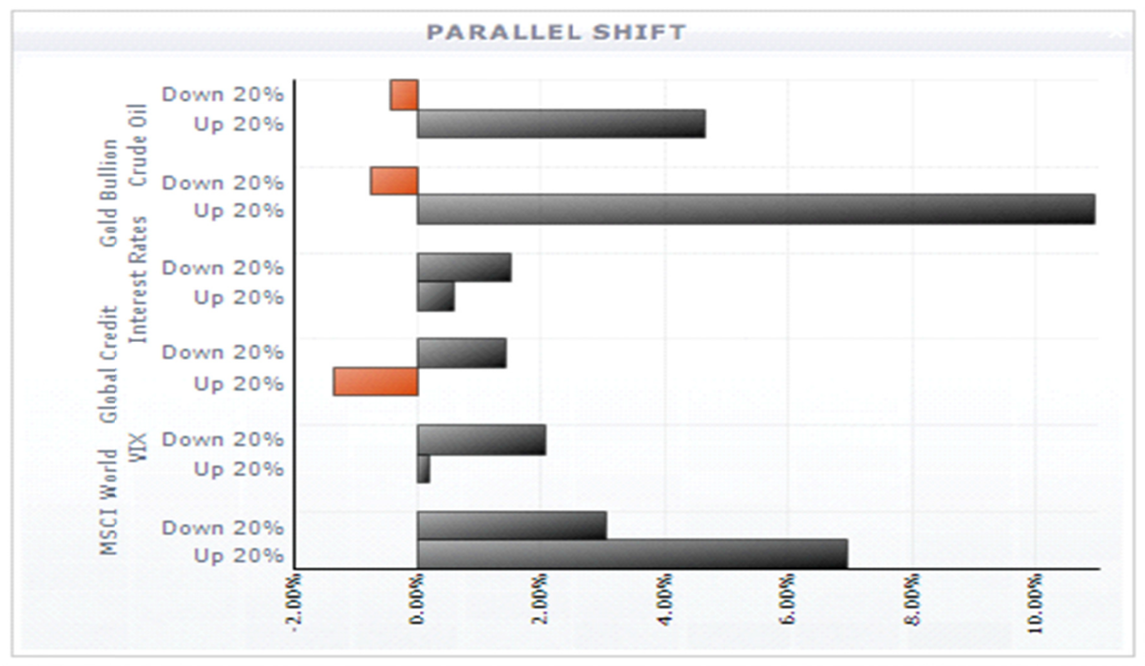


Figure 25

Positive convexity is evident in the fact that in many cases both Up 20% and Down 20% moves in the risk factor result in positive performance for the fund.

We also provide a more flexible tool that allows investors to specify the set of factors (models) to use for analysis, the shock level to apply to all factors. Investors can also chose to switch from using single factor to multi factor model. The screen shot for multi factor choice is shown in Figure 26.

START DATE	8/31/2002	END DATE	10/31/2011	FACTOR MODEL	Main Asset Classes
SHOCK LEVEL	-20.00 %	MODEL TYPE	Multivariate	ANALYZE	

FACTOR	SENSITIVITY	HIGHEST	LOWEST	WORST CASE	SHOCK
ALPHA	0.01	0.00%	0.00%	0.77%	0.62%
MSCI WORLD	0.12	11.49%	-19.91%	-2.41%	-2.43%
VIX	-0.03	90.75%	-32.67%	-3.13%	0.69%
GLOBAL CREDIT	-0.54	11.24%	-17.34%	-6.08%	10.82%
INTEREST RATES	-0.03	109.49%	-93.10%	-2.92%	0.53%
GOLD BULLION	0.23	17.97%	-16.98%	-3.91%	-4.61%
CRUDE OIL	0.12	43.35%	-33.05%	-3.98%	-2.41%
				TOTAL: -21.66%	3.22%

Figure 26

The Worst Case column shown in Figure 26 refers to the worst move in every factor for the fund given the fund's sensitivity to the factor. Depending on the sign in the Sensitivity column the Worst case will be calculated using either the Highest or Lowest historical return for the factor. For example: this fund has positive sensitivity (Beta) to MSCI World. This means that the worst case scenario for the fund is the loss in MSCI World of 19.91% (September 2008). Negative Beta to Global Credit implies that the worst move in Global Credit factor is the positive move of 11.24%.

Switching to Single Factor model allows us to incorporate convexity into the analysis but presents us from aggregating results (Figure 27).

START DATE	8/31/2002	END DATE	10/31/2011	FACTOR MODEL	Main Asset Classes
SHOCK LEVEL	-20.00 %	MODEL TYPE	Univariate	ANALYZE	

FACTOR	ALPHA	SENSITIVITY	CONVEXITY	HIGHEST	LOWEST	WORST CASE	SHOCK
MSCI WORLD	0.70%	0.10	1.07	11.49%	-19.91%	3.02%	3.05%
VIX	0.75%	-0.05	0.09	90.75%	-32.67%	3.22%	2.03%
GLOBAL CREDIT	1.12%	-0.07	-0.28	11.24%	-17.34%	0.00%	1.40%
INTEREST RATES	1.16%	-0.02	-0.03	109.49%	-93.10%	-4.60%	1.51%
GOLD BULLION	0.15%	0.29	1.23	17.97%	-16.98%	-1.28%	-0.79%
CRUDE OIL	0.45%	0.13	0.41	43.35%	-33.05%	0.73%	-0.45%

Figure 27

Market Regime Analysis

Market Regime Models

Market regime analysis allows us to estimate the fund's performance in different market environments/regimes. The analysis begins by constructing a model that breaks down historical market performance into various regimes. There are several ways of constructing the models:

1. *Qualitative assignment of regimes names to various periods (e.g. Boom, Recession, etc.).*
2. *Simple Break down into Up/Down markets.*
3. *Assignment of regimes based on a certain indicator (e.g. level of VIX).*
4. *Quantitative analysis of historical performance.*

Within Transparency Analytics platform we have chosen to use the last three methods. We currently have three market regime models. Our main model is Global Factors Model. This model is based on the quantitative cluster analysis of historical market data. We also provide the model based on Up/Down performance of MSCI World index and a model that is based on the level of VIX.

Global Factors Model

The model uses cluster analysis technique to divide market history into three distinct regimes:

1. *Treading Water*
2. *Bull Market*
3. *Flight to Quality*

The regimes were initially identified by analyzing performance of the main global risk factors in different environment and identifying clusters of similar performance. The performance of these factors in the three different regimes is shown in Figure 28.

Asset	Flight To Quality	Bull Market	Treading Water
MSCI World	-6.93%	3.71%	0.12%
VIX	32.30%	-12.43%	2.32%
Global Credit	-3.70%	3.06%	0.37%
Interest Rates	-9.50%	6.65%	-5.02%
Gold Bullion	2.56%	0.96%	1.11%
Crude Oil	-3.53%	3.52%	1.35%

Figure 28

As we can see the main risk factors have very different average returns in the three regimes. Also different are the correlations of factors in different regimes. Figures 29-31 show the correlations of the main risk factors in Treading Water, Bull Market and Flight to Quality regimes.

Figure 29

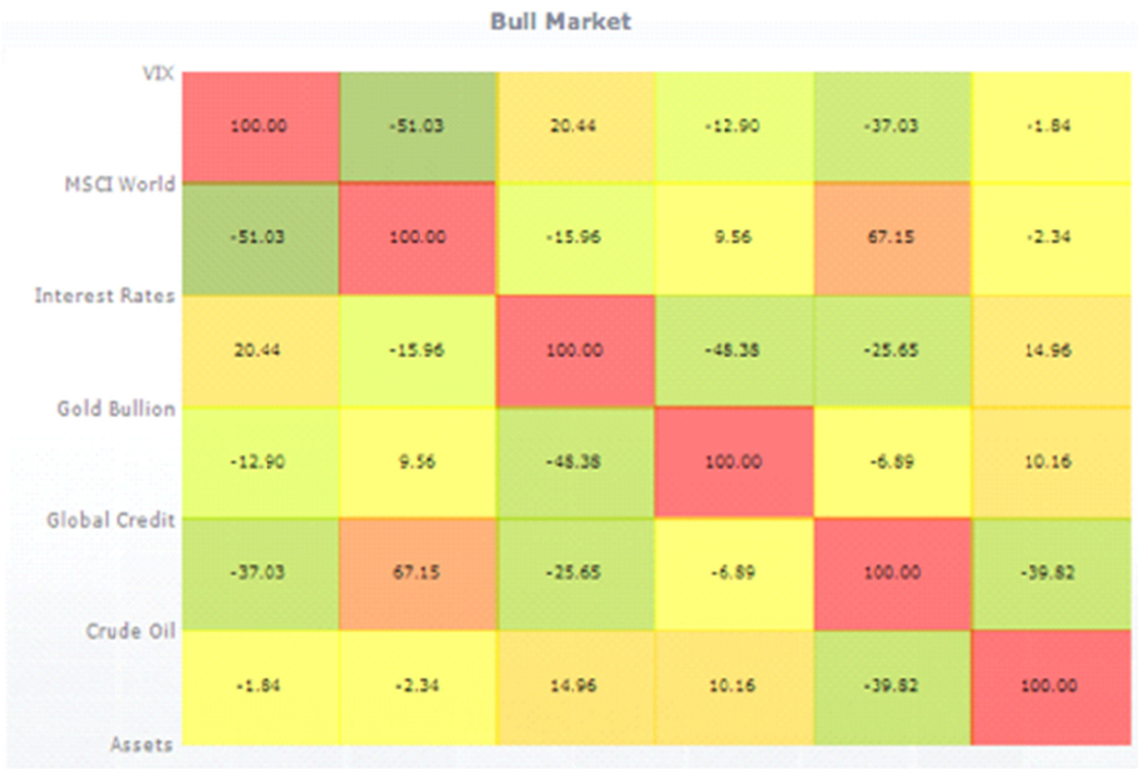


Figure 30

Figure 31

Regime Models have several applications in modeling and analyzing hedge fund performance. Within Transparency Analytics® platform we currently use Market Regime Models as follows

1. *Evaluate the fund's historical performance in different regimes (Figures 32 and 33).*

REGIME STATISTICS

Regime	Avg Ret	Std Ret	Beta To S&P	# Points
Flight To Quality	-1.01%	5.51%	-0.39	12
Bull Market	0.11%	5.55%	-0.70	24
Treading Water	1.45%	3.87%	-0.01	74

Figure 32

Figure 33

2. *Perform Monte Carlo simulation (See below)*

3. *Estimate forward looking returns used in optimization (Currently in development).*

Option Payoff Analysis

Option Payoff Analysis provides us with additional way to put the fund's performance in market regime context. Here we use a simple chart (Figure 34).

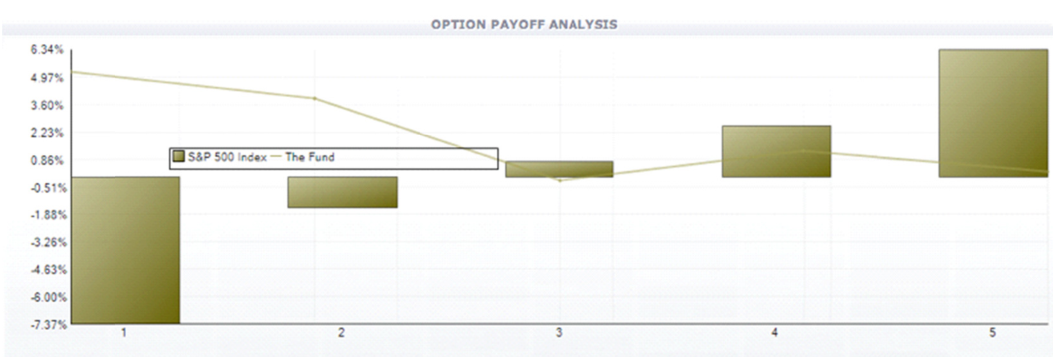


Figure 34

In the chart each bar represents the quintile performance of S&P 500 index. The line represents the average performance of the fund in the same periods. The shape of the line tells in which equity environment the fund is likely to perform best or worst.

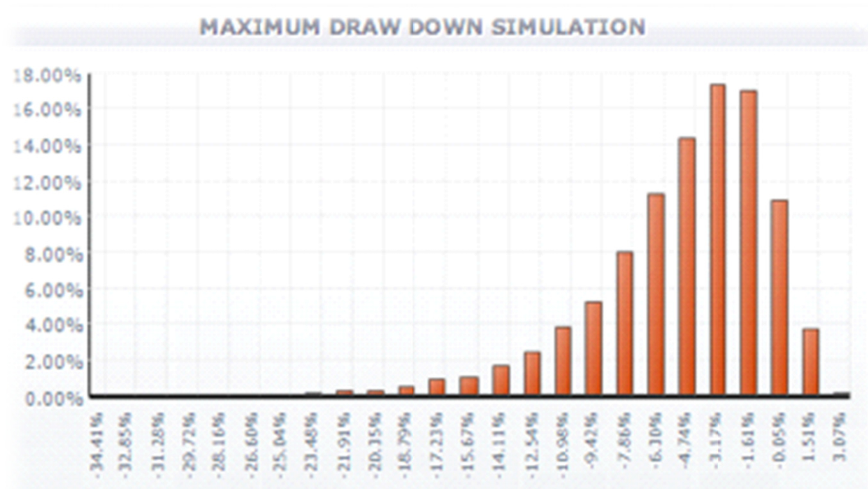
In the example above the fund seems to perform best in the worst quintiles of S&P 500. The shape of the line actually resembles the payoff of a put option.

Monte Carlo Simulation Analysis

Monte Carlo Simulation is a tool that allows us to construct theoretical performance of the fund under many different scenarios. Typical simulation consists of five to ten thousand trials. There are multiple ways of constructing and running simulation. In Transparency Analytics® we currently have two approaches.

Distribution Matching Approach.

We fit every fund's return distribution to Extreme Value distribution. The extreme value distribution provides us with "fat tail" distribution. We then use the properties of the distribution to simulate 12 months of performance over ten thousand trials and estimate the maximum drawdown the fund would encounter under each trial. The output of the simulation is the distribution of likely drawdowns that we can expect from the fund (Figure 35).



MAX DD <=	CUMULATIVE PROBABILITY
-5.00%	48.13%
-10.00%	14.86%
-15.00%	4.48%
-20.00%	1.19%
-25.00%	0.34%

Figure 35

Our more sophisticated approach relies on the use of the market regime model framework described above. The approach consists of several steps.

1. *Select appropriate market regime model.*
2. *Select factor model*

3. *Selected starting regime.*

4. *Estimate average returns and covariance of the selected risk factors under each of the market regimes.*

5. *Estimate fund's exposure (betas) to the selected factors over the entire track record of the fund.*

6. *Simulate the evolution of the market regimes base on the transition probabilities. For each new market regime simulate performance of the risk factors using the appropriate expected returns and covariance matrix.*

7. *Simulate standard no*

8. *Use fund's sensitivities to the factors to estimate the fund's performance.*

9. *Repeat Steps 5 to 8*

The simulation engine provides us with a way to examine different likely outcomes that the fund is likely to achieve. We can examine the distribution of simulated returns and drawdowns (Figure 36).

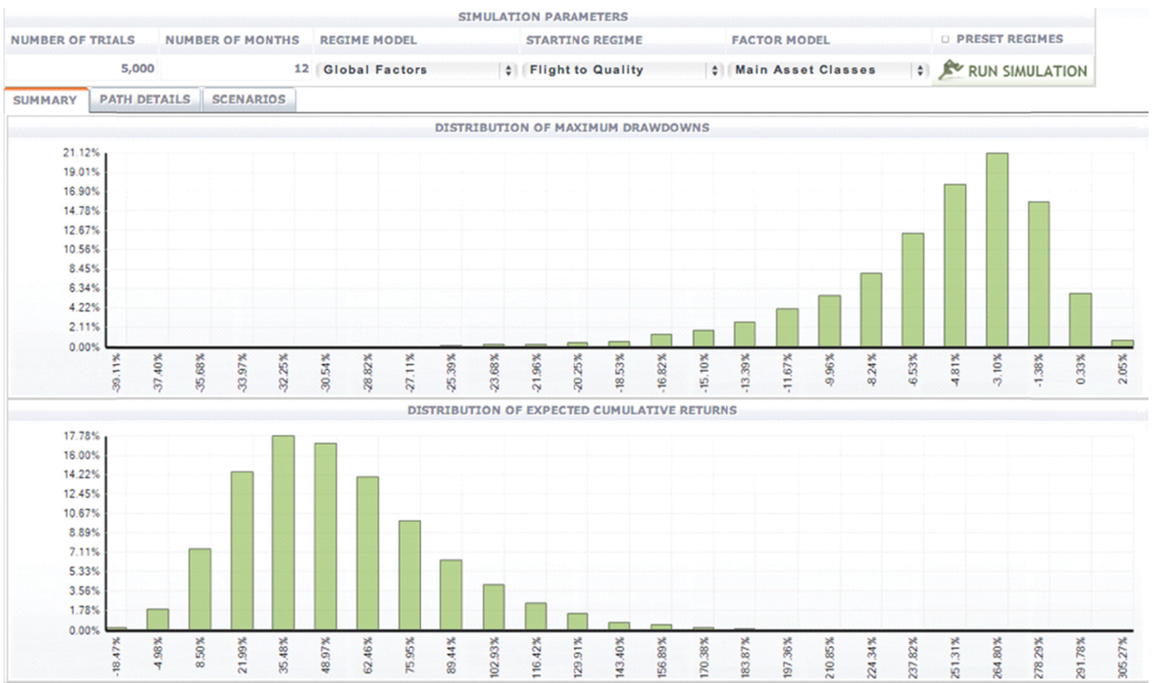


Figure 36

We can also examine individual trials to see what kind of market environment benefits or hurts the fund the most (Figure 37).


FUND PERFORMANCE
215.27%
203.49%
191.71%
179.93%
168.15%
156.36%
144.58%
132.80%
121.02%
109.24%
97.45%
0 1 2 3 4 5 6 7 8 9 10 11 12
SIMULATED REGIMES
Treading Water
Flight to Quality
Bull Market

Figure 37

Σ Address:

Risk-AI, LLC

14 Wall Street, 20th Floor, Suite 2060

New York, NY 10005

Σ Online:

http://www.TransparencyAnalytics.com

http://www.Risk-AI.com

Σ Email: contact@risk-ai.com

Σ Phone: (212) 618-1660