International Standard Asset Management

ISAM

Are All CTA's Created Equal?

May 2013

Alex Greyserman, Ph.D.

www.isam.com

client.relations@isam.com

ISAM

INTRODUCTION

We will demonstrate that a higher degree of correlation is not necessarily associated with a higher degree of similarity of returns.

Similarity of styles (e.g., trend-following) and a fair degree of correlation often lead investors to the inference that all CTA's are in some sense created equal and they really need a small number of managers, perhaps as little as just one, or some kind of "simple system" to get the bulk of the returns of the space. We suggest that the devil is in the details. There is a common misperception that a higher degree of correlation implies a high degree of similarity of returns. We demonstrate that in fact this is not necessarily the case and discuss implications for portfolio construction.

There are clearly some common factors in play, but there are also a number of factors that can cause significant differences in performance amongst managers with generally similar styles. We have previously written about several ways to track the return dispersion of trend-following strategies due to some common factors.[1]

In this paper we extend the analysis by partitioning the trend-following space into several sub-spaces where more details and more sources of return dispersions can be revealed and monitored along the major dimensions affecting trend-following performance. Moreover, corresponding benchmarks can be established for the trend-following programs belonging to each subspace.

We also discuss the portfolio benefits of various subspaces of trend-following, using metrics such as skewness, crisis alpha, and beta, and demonstrate that certain subspaces are particularly more effective in terms of a desirable return profile in the context of traditional institutional portfolios.

---

[1] "Trend Following: The Myth of Return Dispersion", *ISAM Whitepaper*, February 2012.

www.isam.com
client.relations@isam.com

In this paper, in addition to discussing characteristics of each subspace of trend-following, we will also address classifying a given track record into the subspaces.

Additionally we also address the "reverse issue" of classification, i.e., given a manager's track record, what can be said about their inherent exposures to certain types of factors? By categorizing a manager's set of relevant factor exposures, we can also address the issue of style-drift by performing and comparing this analysis over different time periods. We review performance records of a sampling of CTA's and demonstrate some interesting results.

In Section I, we use a simple example to illustrate the relationship between correlation and dispersion. Then, in Section II, we discuss the major dimensions along which an anatomical view of the trend-following space can be presented. Section III describes our methodology of constructing the subspaces. In Section IV, we analyze the characteristics of each subspace, primarily from the aspects of return distribution and crisis alpha. In the end, we investigate how to identify which subspace a given track record belongs to.

I. Correlation vs. Dispersion

Many CTA's have high degrees of correlation, but yet there is an apparent high degree of return dispersion. In order to better understand the relationship between correlation and dispersion, let us take a short detour into simple statistics.

Figure 1 shows the equity curves of three artificially generated assets. By a quick glance it would appear that Asset 1 is much more correlated with Asset 2 than with Asset 3. However, in fact Asset 1 has a -1.0 correlation with Asset 2 and a +1.0 correlation with Asset 3! This is obviously a conceived extreme example, but it does show the dangers of over-reliance on the correlation metric.

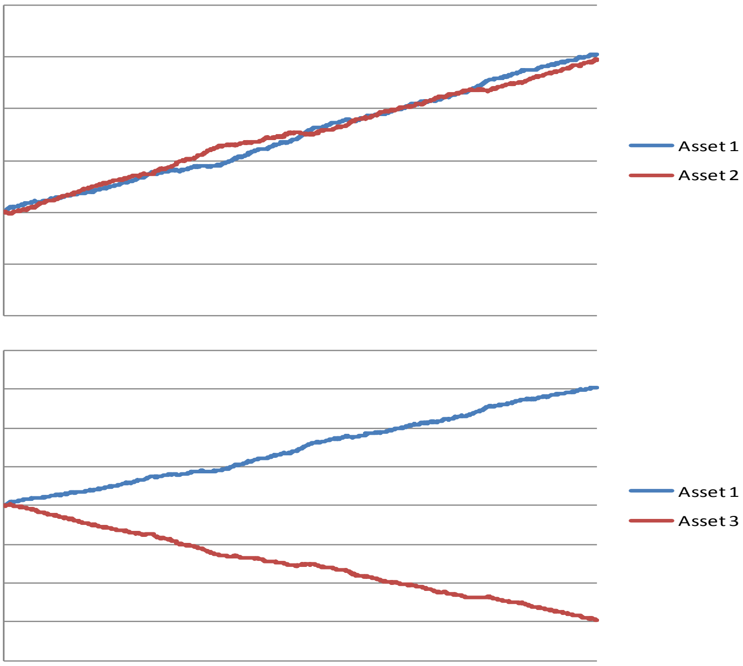

Figure 1: Three artificially generated equity curves illustrating seemingly deceptive correlation values between assets.

Track records with a high degree of correlation can have returns with a high degree of disparity.

From this example one should find it unsurprising that track records with a fairly high degree of correlation, sometimes as high as 0.7 or 0.8 or more, can still exhibit a high degree of absolute return dispersion. For example, the 2012 return ranges from over 30% to below -35% for the CTA managers with at least $1 billion AUM tracked by the Newedge Nelson Report.[2]

Moreover, this simple example illustrates that correlation by itself cannot be used as the only measure to make decisions such as how many managers to have in the portfolio. One cannot infer from the high correlations between the assets (or managers) that they are all created equal and that, at the extreme, only one manager is needed to represent the space.

---

[2] The mean return in 2012 was -1.1% for this group. One should note that these managers are not necessarily trend-following managers, and their leverage or risk levels can be quite different.

High correlations in the trend-following space do not void the necessity of choosing several managers scattered over several dimensions of the space.

In fact, by analyzing multiple combinations of representative track records of various trend-following systems, we can evaluate how the return dispersion diminishes over an investment horizon of multiple years. In Figure 2, we empirically quantify the average interquartile range of investing in *n* trend following programs, where *n* is from 1 to 20 in the study. We can see that, in spite of high correlations in the space, the risk of choosing a single manager is quite high. Several managers scattered over several dimensions of the space are needed to smooth out the performance variability over time.

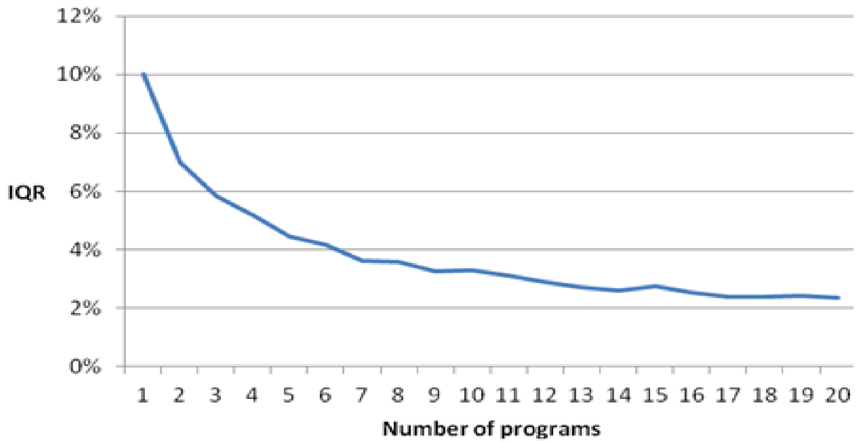

Figure 2: Dispersion of average annual returns diminishes when one invests in more trend-following programs. The vertical axis is the mean interquartile range of annual returns.

II. An Anatomical View

A typical trend-following system has several major components, including signal generation, position management, and risk allocation. Within these components, there are numerous parameter and methodology choices which can exert large impact on the performance.

ISAM

This paper examines three of these aspects in the form of holding horizon, capital allocation, and system bias. Segmenting the trend following space along these three dimensions provides an opportunity to differentiate within the broader strategy.

Holding horizon

The holding horizon is the result of several parameter choices, including the length of lookback window used for identifying trend signals, and the length of rolling window used for calculating market volatility, and possible stop parameters. We divide the holding horizon into two ranges: long horizon and medium horizon.[3] We should point out that this categorization is somewhat artificial and is used for illustration only. A well diversified fund would likely employ a mixture of shorter and longer time frames which would average out to a holding period along this time spectrum.

Capital allocation

Similar to the market capitalization based weights in SPX, trend-following in futures markets can employ a market capitalization based allocation approach as well.

Capital allocation is a second differentiator of portfolio performance. This paper distinguishes between two well accepted allocation methodologies: Equal Risk Weighting and Market Capitalization Weighting. For illustrative purposes, we can look to the world of equities in which the S&P has calculated indices using both methodologies. It is well documented that the equally weighted S&P 500 index (SPW) has historically outperformed the market capitalization weighted S&P 500 index (SPX) over the long term, as shown in Figure 3. Fundamentally, we can attribute this outcome to the greater degree of diversification represented by the lesser liquid markets.

[3] In our experiments, we identify the average holding period of above 100 days as Long Horizon and the holding period between 100 and 40 days as Medium Horizon.

We can observe a similar phenomenon for trend-following in that an equal risk allocation in the long term outperforms the allocation contructed on a market capitalization weighted basis.[4]

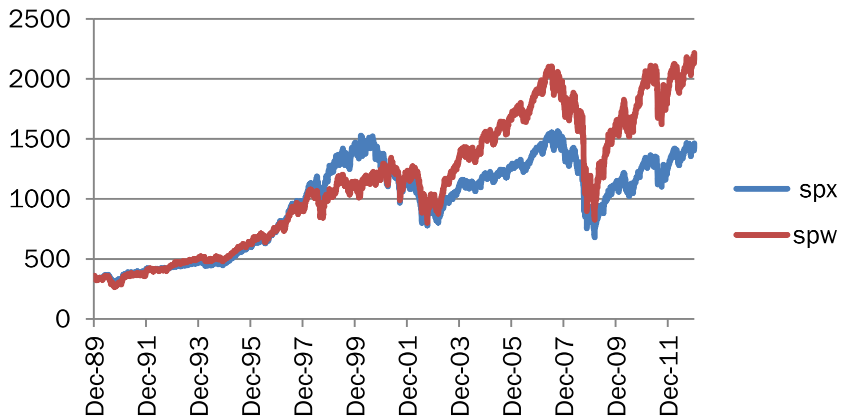

Figure 3: The equally weighted S&P 500 index (SPW) and the market capitalization weighted S&P 500 index (SPX) since 1989.

A fund with a very large AUM likely needs to follow a capital allocation approach based on market capitalization.

In the case of trend-following a futures market, we define the market capitalization as the average daily volume multiplied by the dollar volatility of each market. This metric is a risk based liquidity measure of that market. A fund with a very large AUM cannot allocate capital with equal risk given to markets with vastly differing liquidities, and is likely to follow an allocation scheme closer approximating a market capitalization weighted scheme.

As noted earlier, the additional diversification achieved in an equal risk weighted allocation scheme provides substantial diversification impact to a portfolio.[5] As an example, the market capitalization based scheme in our

[4] For an illustrative example on the performance difference, see "The State of Trend-Following: 2013", ISAM Whitepaper, January 2013.

[5] For empirical discussion on this topic, see "Trend Following: Empirical Findings of Diversification by Less Liquid Markets", *ISAM Whitepaper*, May 2012.

experiments allocates over 60% of capital to the equity index and bond sectors, while the agricultural sector receives only 5% allocation. This highly imbalanced allocation makes the portfolio concentrated primarily on just two financials sectors, and reduces the significant diversification benefit which can be provided by other markets.

Dividing the trend-following space between these two allocation methodologies provides an opportunity to examine the impact of fund size and market depth on the system's return profile.

System bias

A system with a long bias in the equity sector can outperform a symmetric system, but achieves a lower degree of crisis alpha.

With regard to the third parameter choice: system bias, our analysis focuses particular attention on the equity sector. As a by product of fundamental, technical or empirical analysis, some trend-following systems intentionally tilt towards the long side of equities. This can be achieved through various methods including filtering of signals, choice of time frames, choice of parameters, etc. In another whitepaper "Trend Following in Equity Markets: The Cost of crisis alpha"[6], we demonstrated that a trend-following system with a long equity bias would have outperformed a symmetric system at the cost of Crisis Alpha.

By including system bias as the third dimension of return dispersion, we can then partition the trend-following space into the eight subspaces as defined in Table 1. In the next section we discuss the specific methodology of constructing the sub-spaces.

[6] "Trend Following in Equity Markets: The Cost of Crisis Alpha", *ISAM Whitepaper*, August 2012.

We partition the trend-following space into eight subspaces along the dimensions of holding horizon, capital allocation, and system bias.

	Equity Long Bias	Market Cap Weighted	Long Horizon
1	No	No	No
2	Yes	No	No
3	No	Yes	No
4	No	No	Yes
5	Yes	Yes	No
6	No	Yes	Yes
7	Yes	No	Yes
8	Yes	Yes	Yes

Table 1: The eight sub-spaces for trend-following along three dimensions: system bias, capital allocation, and holding horizon. Here, "no Long Horizon" indicates a median horizon.

III. The Methodology

Our study utilizes representative trend-following systems, which are run over a large number of combinations of parameter choices along the three dimensions.

A diversified set of 50 markets from the following four sectors are included in the portfolios: equity indexes, commodities, fixed income, and foreign currencies. The testing period covers 20 years ending in early 2013. A wide array of representative systems comprise manycombinations and nuances of the dimensions defined in Section I, so that each subspace is represented by sufficient samples.[7]

In the next section, we summarize the characteristics of the return streams within each subspace. Box plots are used to illustrate the return statistics in each subspace. Within each box, the central mark (the red line in the charts) is the median, and the edges of the box represent the 25th and 75th percentiles, i.e. the inter-quartile range. The whiskers represent the most

[7] All returns are normalized to an annual risk of 20%. No transaction costs are deducted from the returns.

extreme points in the sample which are not outliers.[8] The individual red plus signs in the charts outside of the whiskers are considered outliers.

IV. The Characteristics

Figure 4 shows the return dispersion in 2012 through the use of these box plots within each subspace. In this particular year, a symmetric system with equal risk allocation and a medium holding horizon (subspace 1) would be the worst performing, while a system with an equity long bias, market capitalization based allocation, and long holding horizon (subspace 8) would have achieved a much higher return. Figure 4 further illustrates that in 2012, the return of a symmetric system with equal risk allocation and a medium holding horizon would likely have been in negative territory (the median is lower than -15%). However, a longer-term system with an equity long bias and an allocation concentrated in equities and bonds could have generated significant positive return: the median return of the analysis showing +10%.

The relative performance across the box plots is quite different between 2012 and 2009.

In contrast, Figure 5 shows the return dispersion in 2009 for each sub-space, where the profile illustrating a symmetric system with equal risk allocation and a medium holding horizon (subspace 1) was among the best: the median return of this subspace was above 15% in 2009.

[8] The outlier boundaries in these charts are 1.5 times of the box height away from the box edges.

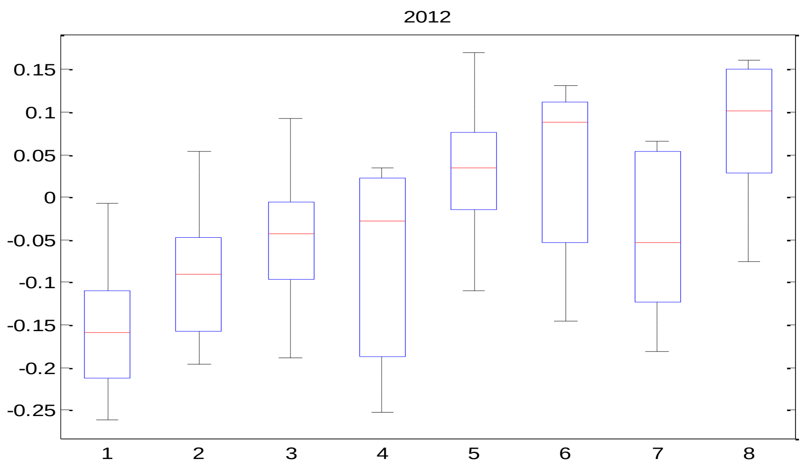

Figure 4: The return dispersion in 2012 for each subspace defined in Table 2. Y-axis is annual return.

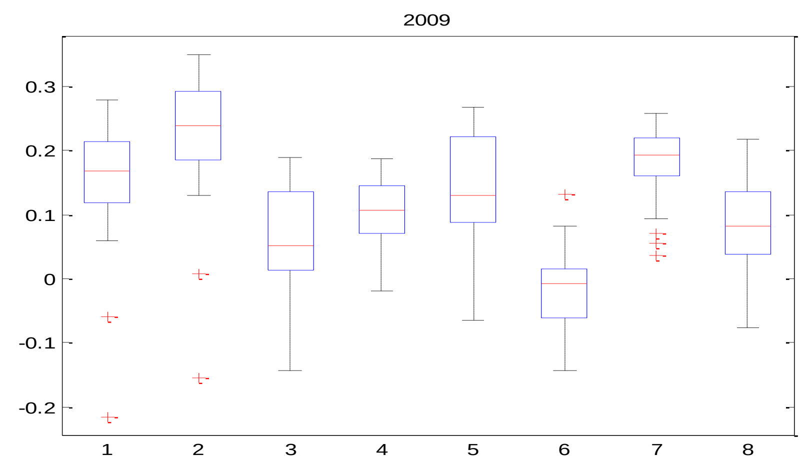

Figure 5: The return dispersion in 2009 for each subspace defined in Table 2. Y-axis is annual return.

Partitioning the trend-following space along various dimensions not only provides reasonable explanations of short-term performance dispersion, but also establishes corresponding benchmarks for performance evaluation.

Partitioning the trend-following space along various dimensions establishes more appropriate benchmarks for performance evaluation as well.

The wide disparity of median results in the subspaces demonstrates the need for different benchmarks for each of the various profiles defined. In the box plots, the red lines indicate the medians of the respective return distributions and can be considered as a form of "trend beta" for the particular parameter profile space. By including more factors, the space can be partitioned to even finer subspaces, as illustrated in Figure 6, with 24 subspaces. This would result in a more granular specification of benchmark information within said profile.

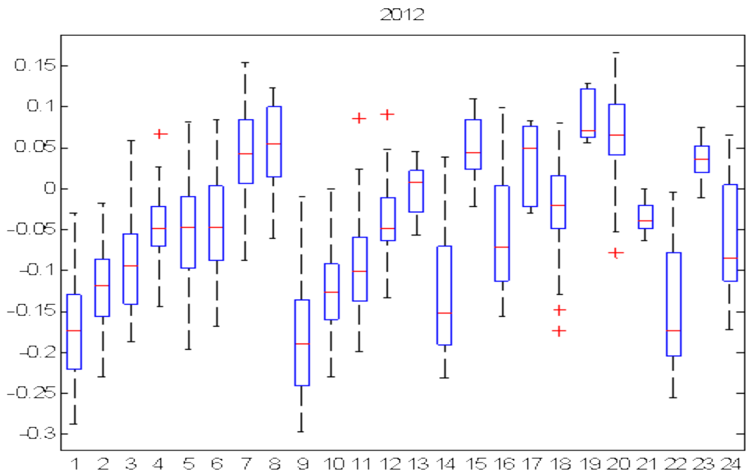

Figure 6: An example of finer partitioning of the trend-following space.

Long-term performance

Having defined the methodology of segmenting the return profiles, the analysis can focus on the empirical long-term performance of each subspace. Figure 7 depicts the return dispersion in the past 20 years within each subspace. Subspaces 1, 2, 4, and 7 have provided the best performance across the past 20 years. All four of these profiles correspond to an equal risk allocation approach. Moreover, we can see that the equity long bias does not act as a performance differentiator over a longer data period.

In the past 20 years, it appears that equal risk allocation along with no system bias achieved better performance.

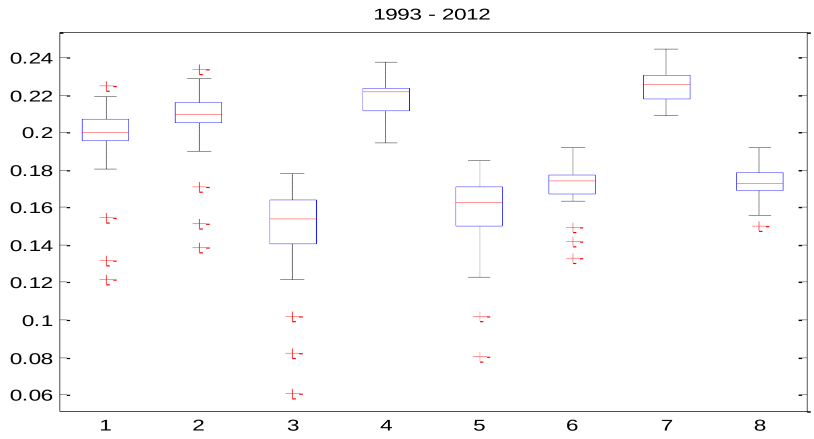

Figure 7: The return dispersion for the past 20 years for each subspace defined in Table 2. Y-axis is annual return.

One of the desirable return characteristics of trend-following is significant positive skewness. However, as shown in Figure 8, the 5th and 8th subspaces exhibit substantial negative skewness. Note that each of these two subspaces are chararcterized by systems with both an equity long bias and market capitalization based allocation approach. The two subspaces with the largest positive skewness utilize a symmetric systems based approach with equal risk allocation methodology (subspaces 1 and 4).

The skewness of returns in the subspaces of equal risk allocation and symmetric systems was the most positive.

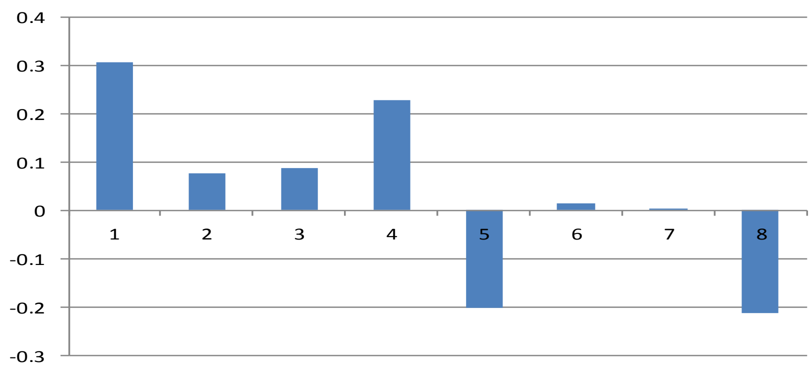

Figure 8: The average skewness of monthly returns of each subspace in the past 20 years.

Crisis alpha

Crisis alpha measures a strategy's performance during equity market crises. It "represents the difference between the original Alternative Investment strategy and the strategy without crisis periods where the performance of the strategy is substituted with an investment in the short-term debt rate".[9] Thus, a higher crisis alpha provides more benefit to a traditional institutional portfolio.[10]

There exist multiple ways to specify a crisis period. In the past, our analyses have used the VIX change as a criterion to identify an equity crisis month.[11] In this analysis however, we simply designate the months in which the MSCI World Equity index had a return of one standard deviation or more below its long-term mean as a crisis month. Figure 9 shows the average of the monthly returns in these crisis periods for each subspace. Once again, subspaces 1 and 4 (no equity bias and equal risk allocation) produce the highest crisis alpha, while the 5th and 8th subspaces (with an equity long bias and market capitalization based allocation) are the worst producers of crisis alpha.

---

[9] Kaminski, K. and Mende, A., "Crisis Alpha and Risk in Alternative Investment Strategies", *CME Group Education*, 2011.

[10] We demonstrated the more significant benefit to an institutional portfolio through the HFRI Fund of Funds Composite Index in "The State of Trend-Following: 2013", ISAM Whitepaper, January 2013.

[11] "Trend Following in Equity Markets: The Cost of Crisis Alpha", *ISAM Whitepaper*, February 2013.

The subspaces of equal risk allocation and symmetric systems achieved the highest crisis alpha.

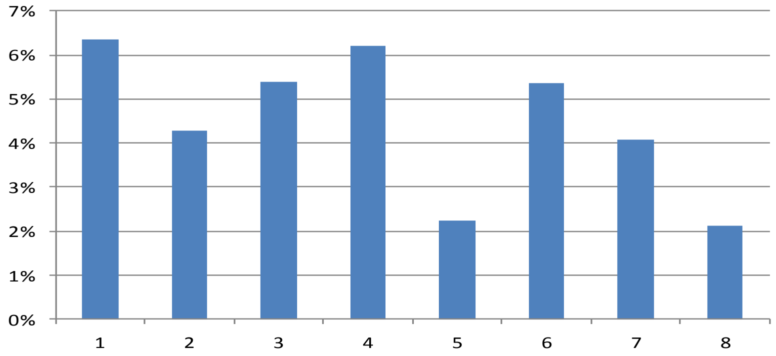

Figure 9: The average returns of each subspace during the months when the MSCI Word Index had a return of one standard deviation or more below its mean in the past 20 years.

Beta

The marginal benefit of Sharpe ratio increase is larger when the correlation becomes more negative.

Relative to Crisis Alpha, the measurement of a strategy's beta is the more commonly used metric with which to gauge an asset's portfolio benefit. A negative beta, or correlation, indicates that, when the benchmark is down, the return of the asset is likely positive, thus providing desirable diversification benefits. In addition to the fact that the portfolio Sharpe ratio improves when the correlation becomes more negative, Figure 10 illustrates the larger marginal benefit of a more negative correlation: the non-linear increase of Sharpe ratio accelerates as the correlation reduction occurs in increasingly negative territory.[12] For example, if the correlation is reduced from 0.3 to 0.2, the Sharpe ratio is increased by 0.04 only. In contrast, the decrease of correlation from -0.2 to -0.3 can increase the Sharpe ratio by almost 0.08.

---

[12] In this example, the two assets are assumed to have the same volatility and the same Sharpe ratio of 1.0, and the allocation between the two assets is assumed to be 1:2.

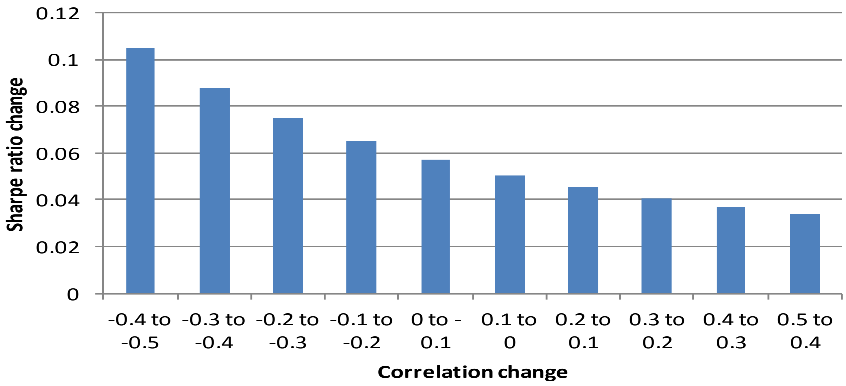

Figure 10: The Sharpe ratio change is different for the same amount of correlation change when the correlation is different.

The subspaces of equal risk allocation and symmetric systems have the most negative correlations with the MSCI World index.

With this undertstanding, we are able to examine the correlation of each subspace with the MSCI World index. Figure 11 shows the average correlation between the monthly returns of each subspace and the MSCI World index in the past 20 years. We can see that subspaces 1 and 4 (no equity bias and equal risk allocation) are most negatively correlated with the benchmark, while the 5th and 8th subspaces (with an equity long bias and market capitalization based allocation) are slightly positively correlated with the MSCI World index.

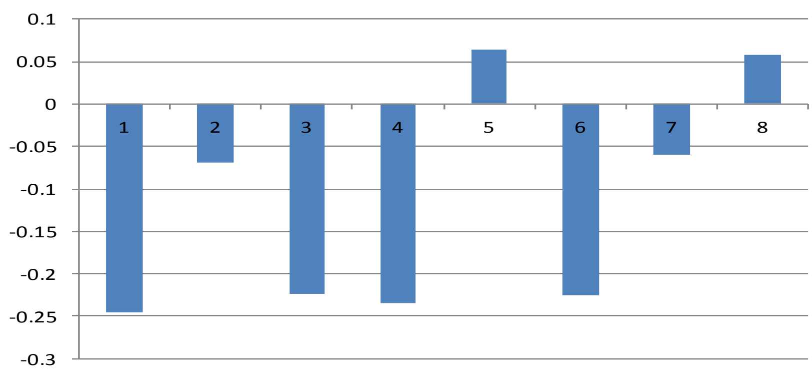

Figure 11: The average correlation between the monthly returns of each subspace and the MSCI World index in the past 20 years.

V. Track Record Classification and Style Drift

Having defined the distinct characteristics of each subspace, we now investigate how to identify the subspace in which a given track record falls. In this section we try to classify eight CTA funds based upon their historical monthly returns.[13]

We can simply use the correlations between a track record and the average returns in each subspace to classify the track record into one of the subspaces.

Many sophisticated methods can be used for this identification problem,[14] but here we demonstrate a simple intuitive method: comparing the correlations between the fund's monthly track record and the average monthly return of each subspace. Figure 12 shows the correlations between the monthly returns of each track record and the average monthly returns of each subspace based on our representative trend-following systems.

It appears that CTA 1 is clearly in subspace 1, while CTA 2 exhibits characteristics of several subspaces. CTA 5, CTA 6, and CTA 8 all appear to exhibit a long equity bias. Another observation is that the average correlations of CTA 3 and CTA 4 with the full array of subspaces are substantially lower than the correlations of their peers. This indicates that these two particular CTA funds may have significant allocations to non-trend-following strategies in their portfolio. These conclusions are consistent with our prior knowledge about these specific track records.

[13] All track records start in June 2001 and end in December 2012.

[14] For example, we tested utilizing the Kolmogorov-Smirnov statistic as a measure of the difference between return distributions, various distance measures between monthly and rolling 12-month returns, and applying Ridge regression to the return series. The various methods may produce inconsistent classification.

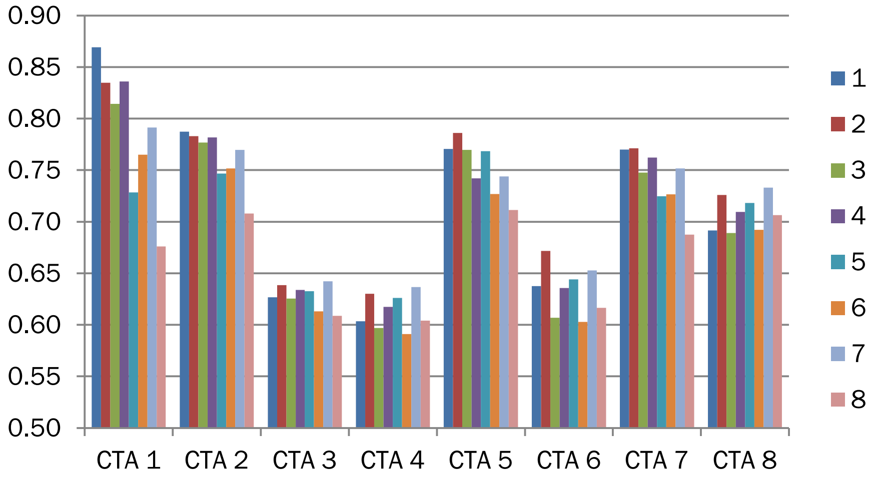

Figure 12: The correlations between the monthly returns of each track record and the average monthly returns of each subspace.

The correlations' variation along the time can be used to identify potential style shift of a trend-following program.

The profile mapping methodology can also be used to identify the style shift of a trend-following program through time as well. As an example, for the same eight CTA funds, we split the track records into two equal time periods. Figure 13 compares the correlations of the track records in the two separate time periods. It appears that both CTA 1 and CTA 2 do not have an apparent style shift between the two time periods. However, the figure reveals striking style shifts for both CTA 3 and CTA 4. It appears that CTA 3 is diversifying away from trend-following more recently (much less correlated with the eight subspaces since 2007), while CTA 4 is in fact moving towards a greater allocation to trend-following and shifting away from the long-equity bias and market capitalization-based allocation (subspace 5) that had characterized it's earlier behavior. Further, the analysis reveals that CTA 5 has apparently allocated more to financials recently (subspace 3 utilizes a market capitalization-based allocation).

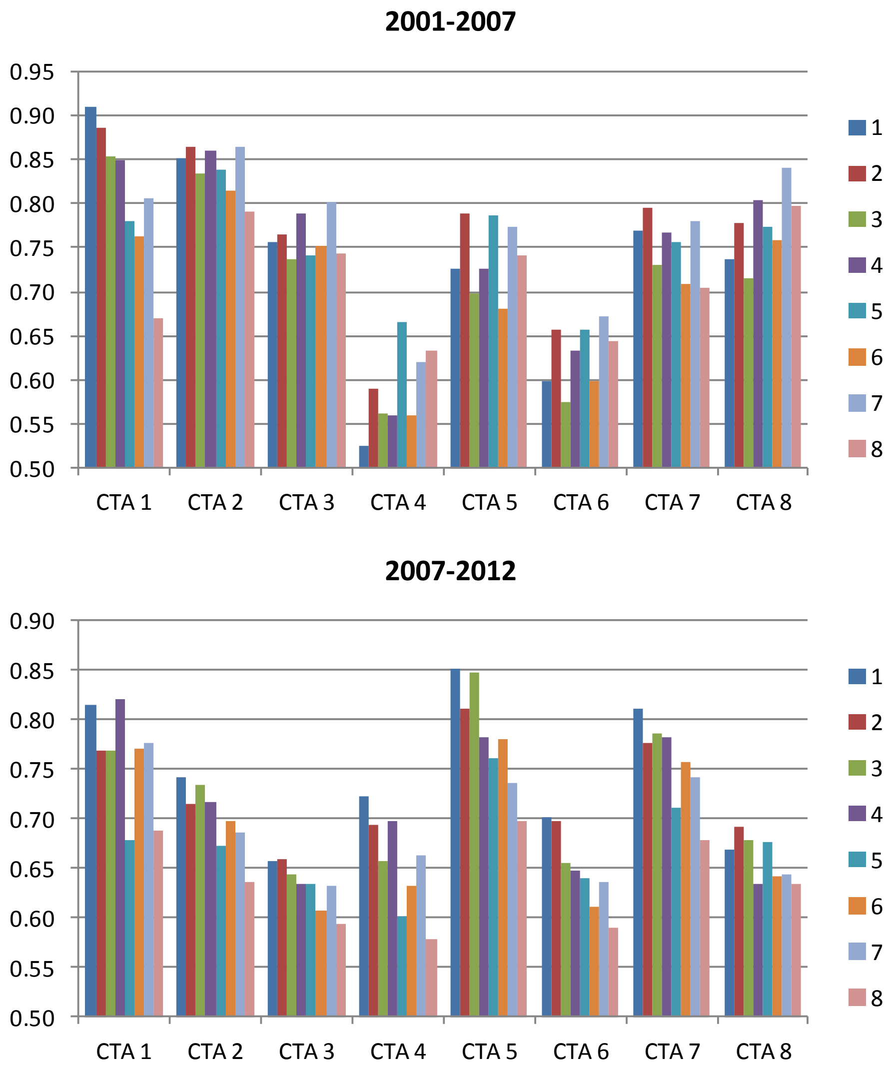

Figure 13: The correlations in two separate time periods between the monthly returns of each track record and the average monthly returns of each subspace.

CONCLUSIONS

This paper proposed a methodology with which to analyze the various drivers of return dispersion within the trend following space. Delineating specific parameter choices and crafting subspaces along various dimensions allows for a greater degree of clarity into the return drivers of this differentiation. The anatomy of the trend-following space in this way reveals sources of short-term return dispersion, and establishes appropriate benchmarks of trend-following performance in each subspace. By analyzing the performance characteristics of each subspace, we showed that a symmetric system (without any intentional directional bias) and equal risk allocation (rather than a market capitalization-based approach) achieves more robust long-term standalone performance, though it may underperform on an absolute basis in a shorter data window. Moreover, as reflected by the return skewness, crisis alpha, and beta, these systems posses a more desirable return profile in the context of a traditional institutional portfolio. Additionally, we demonstrated that simple statistics can be used to classify a given track record to a specific subspace. Therefore, a more appropriate benchmark can be established for the track record, and potential style shifts can be exposed through time. In short, this methodology serves various useful functions for understanding the space and the true nature, style, and benchmark of the players.

ISAM

Important Information:

THIS DOCUMENT HAS BEEN ISSUED AND DISTRIBUTED BY ISAM USA WHEN IT PERTAINS TO U.S. INVESTORS, AND ISAM (UK) LIMITED WHEN IT PERTAINS TO U.K. INVESTORS. (EACH OF ISAM USA LLC AND ISAM (UK) LIMITED IS REFERRED TO HERIN AS "ISAM".) THE INFORMATION IN THIS DOCUMENT DOES NOT CONSTITUTE, OR FORM PART OF, ANY OFFER TO SELL OR ISSUE, OR ANY SOLICITATION OF AN OFFER TO PURCHASE OR SUBSCRIBE FOR ANY FUND OR INVESTMENT PROGRAMME DESCRIBED IN THIS DOCUMENT; NOR SHALL THIS DOCUMENT, OR ANY PART OF IT, OR THE FACT OF ITS DISTRIBUTION FORM THE BASIS OF, OR BE RELIED ON, IN CONNECTION WITH ANY CONTRACT. THIS DOCUMENT IS CONFIDENTIAL AND IS INTENDED SOLELY FOR THE INFORMATION OF THE PERSON TO WHICH IT HAS BEEN DELIVERED BY ISAM. IT IS NOT TO BE REPRODUCED OR TRANSMITTED, IN WHOLE OR IN PART, TO THIRD PARTIES WITHOUT THE PRIOR CONSENT OF ISAM. RECIPIENTS OF THIS DOCUMENT ARE REMINDED THAT ANY PURCHASE OR SUBSCRIPTION TO ANY INVESTMENT PROGRAMME OR VEHICLE MAY ONLY BE MADE SOLELY ON THE BASIS OF INFORMATION CONTAINED IN A FORMAL OFFERING DOCUMENT, DESCRIBING, AMONG OTHER THINGS, THE RISKS ASSOCIATED WITH SUCH INVESTMENT PROGRAMME OR VEHICLE, WHICH MAY BE DIFFERENT FROM THE INFORMATION CONTAINED IN THIS DOCUMENT. NO REPRESENTATION OR WARRANTY, EXPRESS OR IMPLIED, IS MADE OR GIVEN BY OR ON BEHALF OF ISAM OR ITS DIRECTORS OR ANY OTHER PERSON AS TO THE ACCURACY, COMPLETENESS OR FAIRNESS OF THE INFORMATION OR OPINIONS CONTAINED IN THIS DOCUMENT, AND NO RESPONSIBILITY OR LIABILITY IS ACCEPTED FOR ANY SUCH INFORMATION. THE DISTRIBUTION OF THIS DOCUMENT IN CERTAIN JURISDICTIONS MAY BE RESTRICTED BY LAW; THEREFORE, PEOPLE INTO WHOSE POSSESSION THIS DOCUMENT COMES SHOULD INFORM THEMSELVES ABOUT AND OBSERVE ANY SUCH RESTRICTIONS. ANY SUCH DISTRIBUTION COULD RESULT IN A VIOLATION OF THE LAW OF SUCH JURISDICTIONS. IN THE UNITED KINGDOM, THIS FINANCIAL PROMOTION AND THE PRODUCTS AND SERVICES IT DESCRIBES IS DIRECTED ONLY AT RECIPIENTS WHO ARE PROFESSIONAL CLIENTS OR ELIGIBLE COUNTERPARTIES. RETAIL CUSTOMERS MAY NOT RELY ON IT. PAST PERFORMANCE IS NOT NECESSARILY A GUIDE TO FUTURE PERFORMANCE. INVESTORS MAY NOT GET BACK THE VALUE OF THEIR ORIGINAL INVESTMENT. ISAM (UK) LIMITED IS AUTHORISED AND REGULATED BY THE FINANCIAL SERVICES AUTHORITY. **ISAM USA IS REGISTERED AND REGULATED BY THE COMMODITIES FINANCIAL TRADING COMMISSION. IN THE U.S., THIS FINANCIAL PROMOTION AND THE PRODUCTS AND SERVICES IT DESCRIBES IS DIRECTED ONLY AT RECPIENTS WHO ARE QUALIFIED ELIGIBLE PERSONS AS DEFINED UNDER CFTC RULE 4.7.**