Time Frames, Research Quality and Strategy: The Differentiating Factors for CTAs?

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Abstract

Studies dealing with the classification of CTAs have not effectively examined the distinction between the time frame these managers trade and the strategies they employ. Nor have such studies examined the information that rigorous due diligence adds to the process of classifying CTAs. This paper utilizes a set of CTA managers screened from the Barclay CTA (Managed Futures) Data-Feeder database. Returns of these managers are analyzed using variables in this database as well as information collected in an extensive due diligence review. The results suggest that time frame and strategy are distinct factors in the classification of CTA managers. Furthermore, with ratings derived from the due diligence review, research quality is identified as a separate factor affecting CTA returns.

I. Introduction

Over the last decade, Commodity Trading Advisors (CTAs) have become increasingly popular with investors. According to the Barclay Trading Group, global assets under management in managed futures have risen from around USD 5 billion at the end of the 1980s to over USD 150 billion at the end of the second quarter of 2007. This explosion of growth has been attributed to the increased diversification benefits that exist when managed futures are combined with the other major financial assets (see Della Casa et al. (2007)). As the interest in this asset class grows, investors are beginning to understand that CTAs are not a homogenous strategy and that classifying CTA managers facilitates the construction of more diversified portfolios.

A substantial literature has developed that explores various methods of determining the proper classification of hedge funds, but CTAs have been less extensively considered. Most of the previous literature on CTAs has focused on identifying the best managers using historical returns and has concentrated on large, long term trend following managers with long track records. By contrast, a recent report on CTAs by Della Casa et al. (2007) provides a comprehensive illustration of the wide variety of CTA strategies that exist today. They point out that in the current environment, research, innovation and the development of new techniques will increasingly differentiate managers. As part of the search for a better understanding of managers, active due diligence plays an integral role by providing additional information about the trading strategies and other characteristics that contribute to trading success.

The present study adds to the literature on how CTAs can be classified by using the methods applied in studies of hedge funds. In particular, it represents an initial step in incorporating research quality as a characteristic that can be useful in classifying managers. The paper is organized as follows. Section II describes the economic environment that has existed recently. We believe this period is especially interesting in the evolution of trading models and strategies. In section III, we review previous studies that have classified CTA managers. Section IV outlines the selection of managers, the dataset of historical returns and the additional data collected through extensive research on managers. Section V classifies managers by historical returns and interprets the groupings based factors such as

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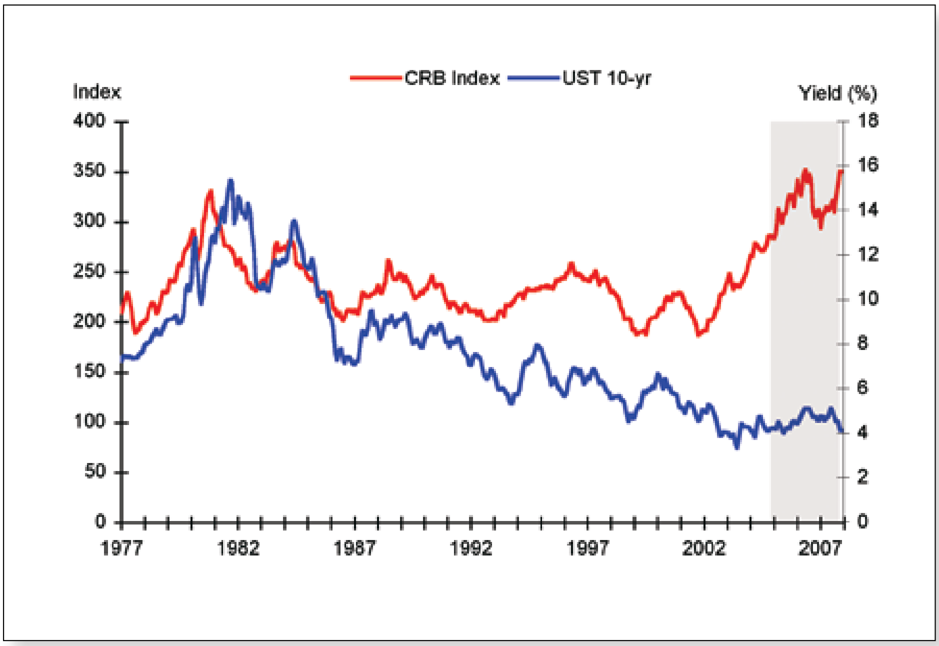
investment time horizon (short, medium, long, and multiple trading time frames), risk management and the value of investing assets to support ongoing research. Section VI discusses these results in the context of the existing literature. Section VII concludes the paper with the implications of our study.

II. Economic Environment

Recent reversals of several long run trends have created challenging economic and market conditions for CTAs. In particular, the commodity markets and government bond markets have undergone such reversals (see Figure 1). In the commodity markets, for example, the path of commodity prices began a marked uptrend as early as 1998. Not until 2004, however, did such prices break out above historical highs. From there the trend has continued with relatively modest and short-lived reversals. Likewise, in government bond markets, the multi-decade rally in bonds reversed as early as 2003, and continued up until the recent flight-to-quality rally.

Figure 1: Commodity Prices and U.S. Treasury Yields



Other noteworthy developments that have either contributed to or been affected by the reversals mentioned above include the following.

- A period of gradual Federal Reserve monetary policy tightening followed by a pause then reversal of that tightening
- Booming emerging market equity prices punctuated by sharp corrections
- A value of the U.S. dollar declining to historically low levels
- Rapid developing country economic growth, solid GDP growth in the U.S. and Europe
- A major credit market dislocation characterized by a steepening of the U.S. Treasury yield curve, rising credit spreads and massive asset price write-downs
- A massive buildup of foreign exchange reserves by developing country central banks, particularly China
- A boom in real estate prices in the U.S. and the U.K., followed by a marked downturn in housing prices, led by the U.S.

III. Overview of Hedge Fund Classification Literature

The interest in hedge funds on the part of investors, finance professionals and academics has grown rapidly in recent years. CTAs have been a distinct object of analysis in only a fraction of these studies. The focus in the following review is on the literature dealing with the classification of CTAs. A brief summary of the literature on classifying hedge funds more generally follows and the section concludes with a short discussion of related issues that hedge fund research has addressed.

The primary approach that researchers have taken in hedge fund classification studies has been the use of linear factor models—such as principal component analysis, factor analysis and regression analysis. The reader can refer to Johnson and Wichern (2002), among others, for a description of these methods. The conceptual basis of the analysis method is the notion that CTAs that adopt similar strategies should have similar returns.

Fung and Hsieh (1997) attempted to identify style factors using the methods developed by Sharpe (1992) in his analysis of mutual funds. They applied Sharpe's style regressions to a sample of 409 CTAs and hedge funds with at least three years of returns as of the end of 1994. Incorporating the effects of trading strategy and leverage, Fung and Hsieh identified five factors or trading styles in their sample. They interpreted these factors as corresponding to the following "dynamic trading strategies": Systems/Trend Following, Systems/Opportunistic, Global/Macro, Value, and Distressed.

By repeating Sharpe's style regressions using the returns for the strategies identified in their factor analysis, they improved the explanatory power (R^2) of the regressions, but only for some of the style factors. Using the trading strategy factors in their style regression improved the explanatory power for the Value style, the Distressed style and the Global/Macro style, but did not significantly improve the explanatory power for Systems/Opportunistic and Systems/Trend Following styles. Returns for different style factors in different market environments (time periods) showed that different strategies respond to different drivers of returns.

Mitev (1998) applied maximum likelihood factor analysis to 20 CTAs covering the period from January 1987 to June 1994. He arrived at a five-factor classification with the factors interpreted as follows. The first factor corresponded to managers who reported using a trend-following strategy. The second factor seemed to be related to risk management and was comprised of managers who employed stops. The third factor was related to trading in interest rate spreads. The fourth factor was related to agricultural commodities. The fifth factor was related to the use of "fundamental and macro-perspective trading." Mitev also performed a cluster analysis on the factor scores (rather than the actual returns) for each manager for each month to determine what types of managers did well in which clusters of months. The first cluster of months is "characterized by negative values of all factors," which he notes does not mean that all managers had negative returns, because they could have had negative factor loadings in those months. In the second cluster of months, fundamental/macro traders performed well and technical traders did not. The third cluster of months was characterized by good performance by technical traders, but poor performance by traders of agricultural commodities. The fourth cluster "positively affects the returns of risk management practices and investment in agricultural commodities."

A number of other studies have used factor models to classify hedge funds. Because they included non-CTA managers, we have not described the results of these studies in detail, although the results are qualitatively similar to the CTA studies. These studies include Agarwal and Naik (2000), Brown and Goetzman (2003), Das (2003), Gibson and Gyger (2006). Other studies, such as Fung and Hsieh (2002) have used indexes of CTA returns rather than the returns of individual managers. Table 1 provides a summary of the studies that pertain most directly to the present study, whether or not they focus on CTAs.

Table 1: Studies of Hedge Fund Classification

Author	Year	Method	Database	Summary of Results
Sharpe	1992	Style regressions	Mutual funds	Asset classes reflect styles of mutual funds
Fung and Hsieh	1997	Style regressions and factor analysis	Hedge funds and CTAs	Trading strategy and leverage improve the style regressions for hedge funds and CTAs
Mitev	1998	Factor analysis	CTAs	Factor analysis enables classification of funds according to strategy
Schneeweis and Spurgin	1998	Regression	CTA and hedge fund indices	Trading style and markets traded are factors affecting the returns of CTA indexes
Agarwal and Naik	2000	Regression (allowing for negative "style weights")	Hedge funds	Allowing negative style weights affects style regressions
Fung and Hsieh	2002	Regression	Trend-following CTAs	Indexes of option strategies produce better style regressions than asset classes for hedge funds
Brown and Goetzman	2003	Regression (generalized least-squares classification-GSC)	Hedge funds	Using different analytical procedures permits the identification of hedge fund styles
Das	2003	Cluster analysis (K-means)	Hedge funds	Applying cluster analysis to hedge fund characteristics produces different classifications than self-descriptions
Gibson and Gyger	2006	Cluster analysis (Partitioning around Methods	Hedge funds	Cluster analysis can help identify departures from self-described strategies

Also, in the expanding literature analyzing hedge funds, classification is one of many topics that hedge fund researchers have addressed. Das (2005) provides a useful discussion of the types of such research. He categorizes this research as: Performance Attribution, Benchmarking, Performance Persistence, and Performance in a Portfolio Context.

IV. Description of Data

A. Sample Selection

The data used in this study were extracted from the monthly CTA returns database of the Barclay CTA (Managed Futures) DataFeeder, one of the largest, most comprehensive sources for managed futures data. The database currently contains monthly historical returns for over 800 CTA programs. The monthly returns and assets under management are reported directly by each manager including a variety of descriptive information. In addition, managers are classified into three self-reported investment strategies: Systematic, Discretionary and Hybrid.

We narrowed the sample size to focus on the managers that are constituents of the Barclay CTA Index. There are currently 428 programs in the Index. Generally, most of the managers in this index have at least of four years of prior performance history. Additional programs introduced by qualified advisors are not added to the Index until after their second year. These restrictions, which offset the high turnover rates of trading advisors as well as their artificially high short-term performance records, ensure the accuracy and reliability of the Barclay CTA Index.

For the purposes of this study, we focused mainly on the larger managers in the Index. This sample set was further reduced to managers that met the following criteria.

- Each of the three trading strategies would be sufficiently represented
- Only the largest program for each trading advisor, as measured by assets under management was selected. Duplicate funds were excluded
- Each program had at least two and half years of trading history
- Each program had a solid business infrastructure
- Each program was open to accept new investments
- Each program provided reasonable liquidity terms to all clients
- Managers did not make excessive use of leverage to generate returns

After application of the above criteria, 56 managers remained in the sample. Of these, one manager had only 34 months of performance and a second manager had only 33 months of data. These two managers were retained and the mean returns for all other months were substituted for the missing data. Further details of the characteristics of the managers selected in this procedure are presented in Table 2.

Table 2: Descriptive Statistics on the 56 programs selected

Total Number of Managers	56
No. of Systematic Managers	40
No. of Discretionary Managers	10
No. of Hybrid Managers	6
Total Assets Under Management	$60.7 billion
Maximum AUM of managers selected	$10.4 billion
Minimum AUM of managers selected	$7 million
Average fund history	7 years

B. The Data

Previous studies of CTA returns have identified a trend-following strategy as a primary factor in classifying CTA returns. A closer examination of the strategies employed by CTA managers, however, suggests that other, previously unexamined factors might also be important in such a classification procedure. A rigorous due-diligence process can provide the basis for a more comprehensive explanation of the stylistic differences of managers within each strategy.

In their guide for CTA due diligence, The Greenwich Roundtable (2006) outlines how an investor can learn more about a manager's style and strategy by asking questions about the manager's business. By conducting in-depth due diligence, investors should be able to identify factors to differentiate managers that have traditionally been classified into similar strategy buckets. This was especially true in the period of 2004-2007. During much of this period, it was difficult for CTAs to be profitable and managers began to exhibit greater differences in their return profiles.

For instance, the time frames that CTAs target vary widely, from minutes to hours to months to a year or more. Some CTAs specialize in one time frame while others run models across multiple time frames. Short term managers use models with greater sensitivity to changes in underlying asset prices and volatility and thus enter and exit positions more quickly than their longer-term, less market-sensitive counterparts.

Another possible differentiating factor is risk management. Some CTA's have sector-level or security-level stop loss limits and profit targets. During periods of extreme volatility, these managers find themselves hitting their stops more frequently and hence losing money on many positions. Other managers allocate risk at the portfolio level in an attempt to avoid market correlations that would cause them to experience the unwanted volatility.

Finally, some managers tend to invest more assets and resources in ongoing research and technology to continue to improve their current systems and find other markets to further diversify their portfolio.

As part of our portfolio construction method, potential managers are included in an ongoing research process. During this process, each manager in the current sample was interviewed on at least two separate occasions, with two or more individuals present in each meeting. Most of the meetings included at least one visit to the manager's home investment office by a due diligence team consisting of at least two representatives assessing the investment strategy of the manager and one representative conducting the operational due diligence review. In addition, the investment team monitored each manager's monthly performance, and looked for changes in investment strategy, style and allocation patterns.

This research process permitted us to categorize the managers in the sample population based on strategy, time frame, risk management and research quality using the criteria outlined below.

Strategy: All managers were classified into one of four major strategies.

- Systematic trend followers
- Systematic non-trend followers
- Discretionary
- Hybrid managers (managers that use a combination of systematic and discretionary investment techniques)

Time frame: Each program was then grouped into one of the following four time frames:

- Long term Long term (longer than 6 months)
- Medium (0 – 6 months)
- Short term (intra-day –few weeks)
- Multiple time frames (combination of any of the above).

Risk management: The risk management strategy of each manager was evaluated in order to identify if the program's risk is managed at:

- Position level – stop loss limits and profit targets for the fund are established at the individual security level
- Portfolio level – stop loss limits and profit targets for the fund are established at the portfolio level
- Portfolio and position level - a combination of the above two strategies

Research quality: On a scale of 1-5 (poor – excellent), each manager was rated based on the company's investment in current and future research and on our assessment of the firm's commitment to the development and evolution of the fund's models and technologies.

Table 3: Summary of data

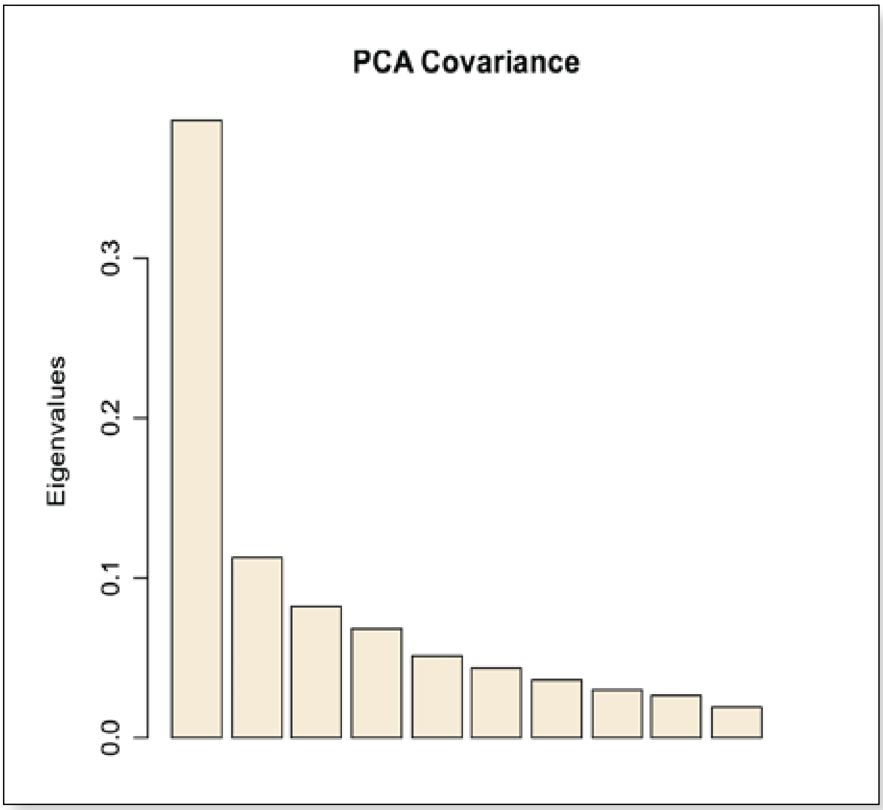
Table 3 shows the number of managers under each of the categories.

Variable	Count
Total Number of Managers	**56**
Number of Managers by Strategy	
Systematic Trend Followers	33
Systematic Non-Trend Followers	6
Systematic - Carry trade managers	1
Discretionary Managers	10
Hybrid Managers	6
Number of Managers by Time Frame	
Long term (6-9 months)	18
Medium (0 – 6 months)	7
Short term (intra-day–few weeks)	12
Multiple time frames	19
Number of Managers by Level of Risk Management	
Portfolio Level	14
Security Level	26
Both Levels	13
None	3
Number of Managers by Quality of Research	
5 - Excellent	2
4 - Good	12
3 - Average	19
2 - Below Average	15
1 - Poor	8

V. Results

To determine the number and type of underlying factors which drive CTA returns, a principal component analysis was performed on the 56 by 56 covariance matrix from the 36 month-return histories for the 56 managers. As shown in Figure 2, over 35% of the variance was explained by the first factor and the first four factors were selected for interpretation.

Figure 2: Plot of Principal Component Eigenvalues



To interpret each factor, the factor loadings for each manager were regressed separately on each of the four classifications of time frame, research quality, strategy, and risk management. In addition, the factor loadings were also regressed separately on the average monthly return and the average monthly volatility for each manager over the 36 month period. A similar method was used to interpret factors two through four.

Of the six regressions run to test the explanatory power of the four categories and two performance statistics, only the monthly volatility (F=46.45 with 1 and 54 DF, p=<0.0001) and time frame (F= 4.01 with 3 and 52 DF, p=0.012) were significant predictors of factor one. A similar analysis of factor two indicated that the only significant predictor was research quality (F= 2.156 with 4 and 51 DF, p=0.087). Investment style (F= 2.157 with 4 and 51 DF, p=0.087) was the only significant predictor of factor three. Research quality was the only significant predictor of factor four (F= 6.26 with 4 and 51 DF, p=<0.0004).

Each of the 56 managers invests using one of four time frames: Long, Intermediate, Short, or multiple time frames. By plotting the distribution of factor loadings for the managers within each time frame separately, one can see if long term managers have higher or lower factor loadings than do short term managers. The box plot in Figure 3 shows that factor one contrasts the long term strategies versus all other time frames. (The reader can refer to Tukey (1977) for a discussion of using box plots to represent data distributions.)

For factor two (see Figure 4), the largest gap is between the highest levels of research, a rating of 5, and the other levels. The difference may indicate that high quality research not only changes the average return, but also qualitatively changes the level of sensitivity to different market opportunities. This would not be surprising given the large commitment of resources to research which might not only improve the quality of modeling, but also facilitates different types of modeling (for example machine learning algorithms such as genetic algorithms, neural networks) and improves risk management. Factor four (Figure 5) also contrasts the top research shops versus all others.

Factor three (Figure 6) contrasts trend following strategies (S1) versus countertrend strategies (S2). Discretionary and hybrid strategies are intermediate between these two systematic strategies.

Figure 3: PCA Factor 1 vs. Time Frame

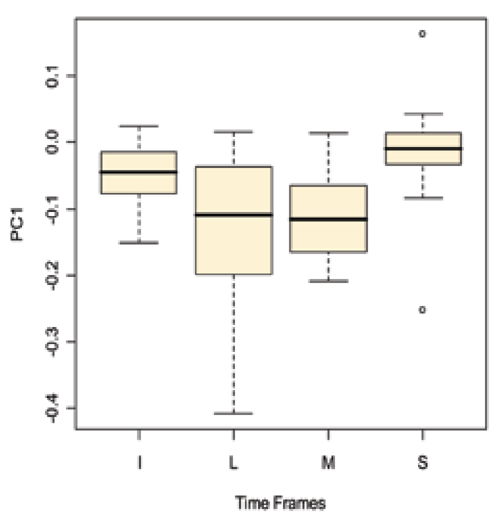


Figure 4: PCA Factor 2 vs. Research Quality

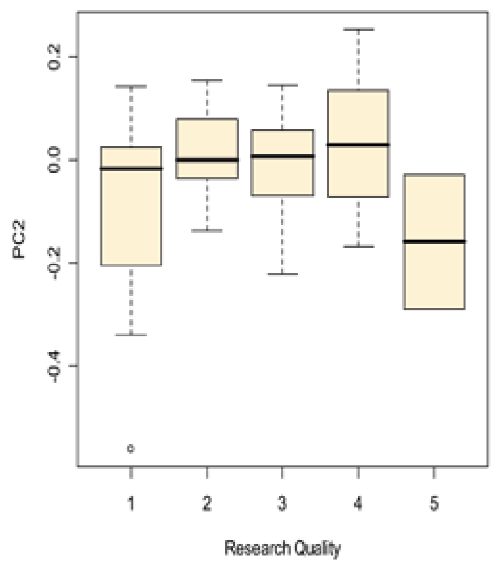


Figure 5: PCA Factor 4 vs. Research Quality

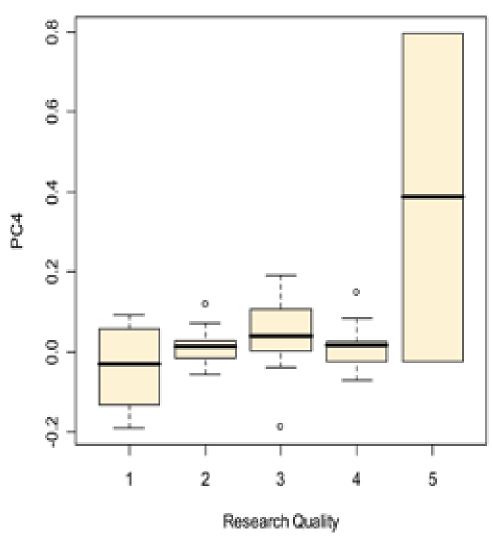
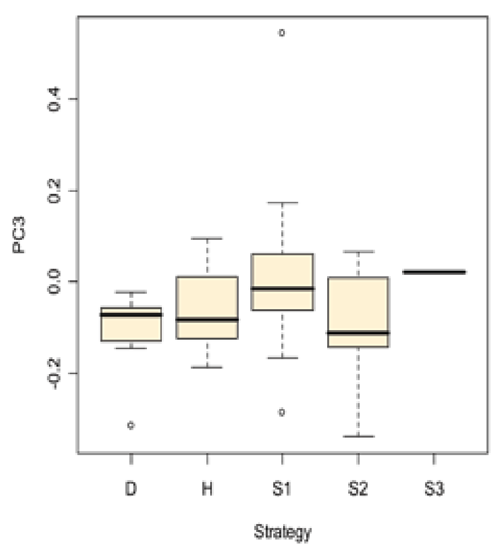


Figure 6: PCA Factor 3 vs. Strategy



Similar analyses and interpretations were also obtained using a principal components analysis of the correlation matrix. Factor rotations yielded the same factor structure except that the interpretations of factor two and three were exchanged.

The differences in performance in the long-term versus shorter-term managers in factor one can be highlighted by examining the dates that were highlighted by the factors scores from the principal components analysis. Each of the 36 months in the original 56-manager, 36-month matrix of returns receives a score on each factor. A high score[3] on factor one indicates a month during which the managers with a high loading on the first factor usually performed well. By contrast, managers with low loadings on the first factor usually performed poorly. A month with a low score on factor one is usually one in which a manager with a high loading underperforms.

To highlight the relationship between the manager loadings and the monthly scores, the five programs with the highest loading on factor one were selected and their returns for each month were averaged to create a 36 month history. The group returns were plotted in Figure 7.

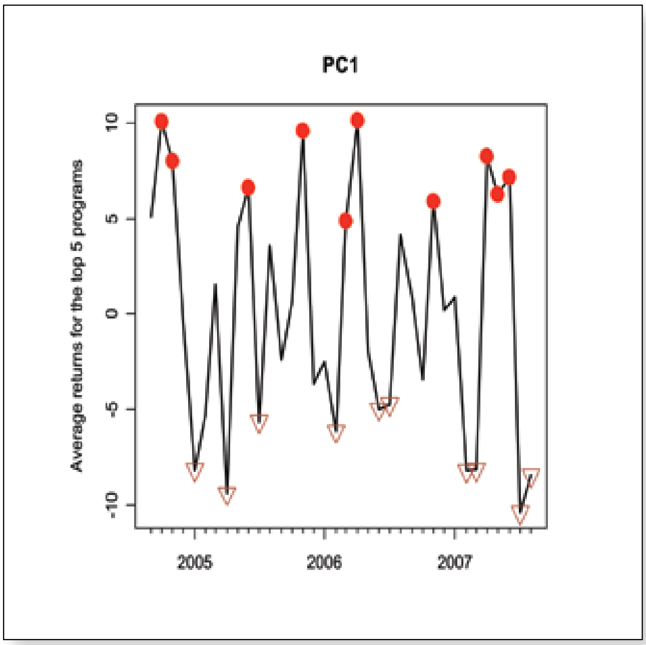


Figure 7: Plotted Returns for the Five Programs With Highest Loading On Factor One

In the Figure, the ten dates with the highest scores on factor one were highlighted as were the ten dates with the lowest scores. The dates are listed in Table 4 along with noteworthy market events with the month.

The market events show that the bottom scoring months were characterized by changes in Fed policy and by severe dislocations in markets that affect liquidity in the time period. The announcement effects of actual changes in Fed policy, whether expected or not, can affect trading in a variety of markets. Periods when abnormally poor liquidity affects some markets and affects the correlations with a broader set of markets are those that most trading strategies are least able to deal with. These are considered the markets that offer the least opportunities and greatest risks for managers with long time horizons. By contrast, the bottom scoring months were those of recoveries following major market events. These were months in which managers with long time horizons can take advantage of trends.

[3] Because the sign (scaling) of the factor loading is arbitrary in principal component analysis, we have chosen a sign that facilitates the explanation of these results.

Table 4: Analysis of Important Months

Bottom 10 Months		Top 10 Months	
August, 2007	Global credit crisis; flight to quality in U.S. Treasury market	April, 2006	Sharp decline in U.S. dollar; global inflation concerns; sharp rise in copper futures
July, 2007	Global credit crisis; flight to quality in U.S. Treasury market	November, 2004	Spike up in oil prices
April, 2005		November, 2005	
January, 2005		October, 2004	Spike up in oil prices
February, 2007	Subprime mortgage concerns	April, 2007	Deterioration of global credit conditions
March, 2007	Subprime mortgage concerns	March, 2006	
July, 2006	Fed on hold	May, 2007	Deterioration of global credit conditions
February, 2006		June, 2007	Deterioration of global credit conditions
June, 2006	Last Fed rate hike; EM equity market correction; peak in UST 10-yr rate	June, 2005	
July, 2005		November, 2006	Congressional elections change control of U.S. House and Senate

Table 5: Market Indicators

Indicator	Description
USTW$ Index	Trade-weighted value of the U.S. dollar
GT2 Govt	Two-year U.S. Treasury Bond yield
GT10 Govt	Ten-year U.S. Treasury Bond yield
CRY Index	Reuters/Jeffries CRB commodity index
CL1 Comdty	Crude oil futures price
SPX Index	Total return on the S&P 500 stock index
VIX Index	CBOE S&P 500 option implied volatility index

* All variables were measured as the monthly percent change, except the VIX which was measured as the monthly high close of the index.

To identify market indicators that might be closely related to each of the factors, the factor scores were regressed on several market indicators. These indicators, listed in Table 5, were selected as those that might be related to the instruments and strategies utilized by CTAs. This analysis only yielded significant results on factors one and three. All others yielded no significant predictive values. For factor one, the monthly total return of the S&P500 ($F=12.76$ on 1 and 34 DF, $p=0.001$) was the best predictor of the factor scores. The scores for factor three were best predicted by the maximum market volatility as indicated by the highest level of the VIX within each month ($F=12.08$ on 1 and 34 DF, $p=0.001$). None of the selected market indicators predicted the monthly scores for factors two or four.

VI. Discussion

The results are both consistent and inconsistent with the studies by Fung and Hsieh (1997) and Mitev (1998). On one hand, the findings of Fund and Hsieh and Mitev show strategy to be the most important differentiator of CTA returns. In contrast, we find time frame as the main differentiator with strategy relegated to the third factor. These findings may not be contradictory since the largest group of CTAs in the previous studies were long-term trend followers, so it was impossible to distinguish between the strategy (systematic, hybrid, or discretionary) versus their trading time frame. The set we analyzed had both long-term and short-term systematic managers along with non-systematic managers with a range of time frames.

The results also support the notion that both risk management and research quality are important characteristics for classifying CTAs. Other studies, such as Mitev (1998) identified risk management as a factor, but no other studies have identified research quality. Given the market environment identified earlier for the period of this study, managers that score high on research quality are likely differentiating themselves in their ability to spot opportunities in the markets in which they trade.

From the loadings on factor one, the first factor was related to the time frame of the manager's investment style. Furthermore, the factor scores associate factor one with returns on the S&P 500. Together, they indicate that managers with longer time frames were adversely affected during months in which the U.S. equity market drops.

A similar analysis of factor three suggests that trend-following, systematic managers profit most in periods of high volatility. This finding is consistent with Fung and Hsieh (2001). They used look-back straddles to model CTA returns. That model is also sensitive to market volatility.

The correlation of the factor one scores with an equity market index raises a question as to why there is the absence of significant correlations with the other interest rate and commodity indices. Although many of the managers trade equity indices, as a group, they have even larger exposures to interest rates, currencies and commodities. Why then is there only a relationship to equities and not to the other markets? One possibility is that the equity indices are a surrogate for general market liquidity, so the long term managers are most affected by drops in liquidity.

VII. Conclusion

This study highlights the benefits that can be obtained from a rigorous due diligence process in selecting CTA managers. In particular, this study demonstrated how due diligence can lead to better classification of CTA managers by helping investors understand the separate effects of time frame and strategy on the managers returns. Until now, CTA classification has considered trading strategy and time frame as a single style factor.

The set of managers described in this study were selected from the Barclay CTA (Managed Futures) DataFeeder database according to specific criteria for possible inclusion in an actual investment portfolio. The database contained information about both the time frame and the strategies employed by these managers. But it was a rigorous due diligence process that led to a better understanding of the differences in the time frames and strategies employed by these managers.

In the principal component analysis of the returns, separate factors were found to be interpretable as time frame and strategy. These results both confirm and extend past research that identified a distinct effect of strategy, but do not consider distinctions among time frames.

The due diligence process also permitted the evaluation of the quality of research conducted by each of these managers. In the analysis, research quality was identifiable as a distinct factor with managers who excel in research distinguishing themselves from others in our sample.

For systematic approaches in particular, part of the manager's competitive advantage may be dependent on quantitative skill and technological resources, but an equally important skill is a manager's capacity to keep up with the changing investment environment. A potential investor can best assess this by questioning managers on all aspects of their business. Without research into these issues, neither the influence of research quality nor the distinction between time frame and strategy would have been identified.

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