

# Managed Futures Strategies

- Support Vector Machines as a Due Diligence Tool

**Author – Amira Roula**

21272@student.hhs.se

Thesis submitted to: Fransesco Sangiorgi

*Stockholm School of Economics*

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Department of Finance

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# Abstract

In this paper, we have used the Support Vector Machine (SVM) method for classifying managed futures strategies, an exiting way of automating part of the due diligence process.

Previously used methods for classification have been lacking, and the ones tested (factor models) have been based on assumptions which do not accommodate for the return distributions of managed futures and the hedge fund industry overall (i.e. IDD and normal distribution assumptions, and linearity).

The SVM method is not dependent on distribution assumptions, and is a process which can automate the classification part of a due diligence process.

When tested on the managed futures data at hand, the SVM showed a certain amount of misclassification by funds tested.



# Chapter 1

## Introduction

As of the first quarter of 2012, the managed futures market size was estimated to be \$328.38 billion (BarclayHedge, 2012), an increase of 151.38% since 2005.

It is an exciting, growing market, which has as of yet received very little academic attention. Maybe, it is because managed futures is an incredibly niche market, a sub-category of hedge funds, which in turn is a sub-category of the financial market; managed futures constitutes 18% of the hedge fund industry, which in turn constitutes 3% of the financial market.

For those investors who do find their way to the managed futures niche, trying to pick the right managed futures program and manager (or Commodity Trade Advisors, CTA:s, as such managers are also called interchangeably) has not been an easy task, a task which does not get any easier seeing to the selection risk involved (Amenc et al, 2005) and the transparency issues marring the hedge fund industry overall. This has led to the process of choosing a manager and fund somewhat of a quest to find the Holy Grail.

The problem of misclassification when conducting peer analysis and a due diligence process is costly. Choosing the wrong manager and fund can be highly detrimental, and yet, research devoted to style drift and misclassification has not presented investors and practitioners a way to deal with the problem. Focus has been on whether such misclassification exists at all. Yet, how does one alleviate the problem without incurring too much costs? Is there a simple method one could apply, to conduct a peer-analysis or a stand-alone due diligence on a manager, a method which will point out if a fund is victim of misclassification and style drift? Yes. And that is what this paper will focus on: a learning algorithm called Support Vector Machines (SVM), a method which has been used to some extent on text and image

recognition but has of yet received scant attention in financial academic literature.

SVM has not been, to the best of this author's knowledge, used to investigate the CTA program strategies used by managers and whether they follow the strategies specified. SVM has in financial academic papers mainly been used to test predictability (Abdu & Nasereddin, 2011; Cao & Tay, 2001; Cao, 2003; Gavrishchaka & Ganguli, 2003; Kim, 2003). Seeing to the great importance and impact a chosen strategy can have on a portfolio, it is paramount that the manager entrusted sticks to the strategy claimed to be followed.

Will the Holy Grail of the hedge fund industry, of finance in general, ever be found? Probably not, but the process of choosing profitable funds can be improved.

## Chapter 2

# Misclassification, style drift and peer analysis

Misclassification has been a bane for investor returns, as both un-intentional (in terms of self-classification being error prone) and intentional style drift (ex. style drift might follow fund flow) make peer analysis an impossibly difficult and unreliable task. The risk style drift entails can be substantial, as a change in strategy and style changes a fund's risk profile. It's one thing if a style or strategy change is part of a fund's or manager's way of trading, and when the investors are notified of such dynamic strategy and style shifts. It's a whole other matter with misclassification.

Looking at how the managed futures market has changed over time, due to factors such as regulatory and technology changes (Scheenweis et al, 2013), the strategies used in general will change as well. It is of importance to the investor to know, how the chosen funds and managers adapt to such changes.

Self-classification is being extensively used as a qualitative classification tool, as there is no agreed upon quantitative method to classify funds. Hedge fund providers also have their own ways of classifying funds, fund labels that vary between providers in numbers and nature.

Peer analysis is traditionally conducted using correlation analysis (Abrams et al, CME Group; Fung & Hsieh, 1997). A correlation coefficient is however nothing but a scalar, and the question to ask oneself is: how much information does this scalar give you in terms of figuring out which styles the managers use? This scalar will not tell you directly, which style the manager is using. The use of factor models as well as benchmarking to indices's are also commonly used, both with their own individual problems. The factor

models will be discussed in the next chapter. Indexes as benchmarks pose a great problem both from a style drift perspective and from a classification perspective; conducting a peer analysis using an index as a benchmark raises the questions: does the index truly reflect the available diaspora of strategies well enough? Does it take into account the fact that the funds it includes apply dynamic strategy changes? There are other issues as well, such as the choice of track record length, selection criteria, weighting schemes and re-balancing; these differences in competing indexes can lead to reported monthly return differences of more than 20% (Amenc & Martellini, 2002).

As has already been pointed out (Bianchi et al, 2005; Gibson & Gyger, 2006; Maillet & Rousset, 2001; Markov et al, 2007; Kat & Palaro, 2005; Boyson et al, 2006), using linear models to analyze data which is not normally distributed is quite problematic. The returns of managed futures are not IID (independent and identically distributed), nor can they be analyzed using linear models.

Another problem faced when using traditional models in peer analysis is the fact that these models are adapted to the strategies of asset classes such as equities and mutual funds, which are less dynamic and do not use leverage to the extent hedge funds and managed futures do.

Using non-linear models to classify hedge fund strategies is not new (Baghai-Wadji & Klocker, 2006), yet none of these models have been specifically adopted as a tool for due diligence activity. Neither has an easy way of implementing these models been presented.

## Chapter 3

# Can classification be conducted with traditional models?

Learning algorithms are not traditionally used for categorization in finance; classification per se is itself uncommon, and practically unheard of when it comes to due diligence. This paper argues that the classification part of the due diligence process can be automated, and that it preferably be done using learning algorithms.

What other models might one consider when classifying managed futures funds and hedge funds? As was mentioned in the previous chapter, factor based models have been a popular choice, due to their simplicity. Fung and Hsieh (1997) wrote an article about using factor models and factor analysis in their quest to classify funds. A definition of what factor analysis is now in order: factor analysis is based on a process using correlations. You might have a hypothesis that these correlations are engendered by one or several reasons; in factor analysis, these reasons are called factors. There are two types of factor analysis one can conduct: exploratory and confirmatory (i.e. hypothesis testing) factor analysis. Exploratory factor analysis is mainly used when there is no hypothesis, when the researcher simply wishes to find the underlying factors .

A similar, related method to factor analysis would be the principal component analysis (PCA). The two methods yield similar results, but there is a large conceptual difference between the two; PCA expresses the factors as linear combinations of the variables, while factor analysis does the opposite, i.e. expresses the variables as linear combinations of factors. Though it initially is stated in the article of Fung and Hsieh (1997) the use of factor analysis, it is actually a PCA that the authors conducted.

For the sake of comparability, a PCA is conducted on the data before continuing with introducing a new, non-linear way of classifying funds. The data analyzed contains 261 funds in a 73 month period (January 2006 - January 2012). The result shows that 47.93% of the variance in the data is explained by 2 principal components. Using the same methodology as Fung and Hsieh (1997), "style factors" are constructed using the hedge funds most correlated with the two components. Looking at the strategies stated by the funds in [iasg.com](http://iasg.com), the first "style factor" can be connected to a strategy combination of "counter-trend" and "trend following", whilst the second factor was connected to the trend following strategy only. Interpreting the data from a PCA perspective, the main strategy which explains most of the returns of the analyzed funds is the trend following strategy. When classifying managed futures using PCA, investors could thus choose to use only two categories; trend-following and non-trend-following.

As a second step, a regression on the factors obtained from the PCA along with the 8 factors as introduced in the Fung and Hsieh (1997) paper is conducted. The additional 8 factors used are the MSCI US Equities Index, MSCI Global Equities Index, MSCI Emerging Markets Index, the US 10 year Government Bond Index, E. Capital Global Government Bond Index, the 1 month Eurodollar, gold prices and the Trade Weighted US Dollar Index.

Looking at the results in Table 5.2, we see that the most of the obtained coefficients are too small to be economically interesting, where the  $R^2$  of the two new factors are 27.42% and 14.86% respectively. The coefficient of the 1 month Eurodollar seem to explain the two factors somewhat, as well as the coefficient of the dollar index. One would expect the other factors (ex. commodities) to explain more of the newly obtained ones, yet that does not seem to be the case.

As mentioned by Fung and Hsieh (1997), the regression of this sort on managed futures data is sensitive to extreme outliers; as we will see in the next chapter, the returns of managed futures have distributions including such outliers.

**Table 3.1: Using the Sharpe asset factor model on the factors obtained using PCA. The betas, in the following order, are connected to: MSCI US Equities Index, MSCI Global Equities Index, MSCI Emerging Markets Index, US 10 year Government Bond Index, E. Capital Global Government Bond Index, the 1 month Eurodollar, gold and the Trade Weighted US Dollar Index.**

Factor	$R^2$	$\alpha$	$\beta_1$	$\beta_2$	$\beta_3$	$\beta_4$	$\beta_5$	$\beta_6$	$\beta_7$	$\beta_8$
Factor 1 (mix, trend-following & counter-trend)	0.2742	0.8370	-0.0077	0.0058	0.0014	-0.000382	-0.000808	-0.1576	0.0026	0.0897
Factor 2 (trend-following only)	0.1486	5.3563	0.0027	-0.0040	0.000482	0.000282	0.000004	0.1927	0.000064	-0.04326

It is important to note that the components when calculated are originally not connected to any particular fund; checking for correlation between the components and the funds, as well as looking for which strategies are used by the funds in question are additional steps one need to take to get to the "style factors" described above. This process is time consuming. The exercise of using PCA to extract the most commonly used strategy is an interesting one, yet it only provides information relating to the total variance of the funds. No actual classification process has been conducted, only a reduction of the variables available (which is the way PCA is mainly used, as a variable reduction tool). In our case, we have reduced the amount of strategies from 13 to 2.

As stated by Fung and Hsieh (1997) in their article, the data they analyze exhibit nonlinear correlations, making interpretations and generalization difficult. The PCA as well as the Sharpe style regression was not intended for classification purposes; the authors used a market regime type of analysis for that attempt (something which is very interesting to look into in more detail in future papers), an exercise which was not statistically validated.

One way of obtaining actual classification of funds can be conducted using learning algorithms, something which is discussed in the next section of this paper.

# Chapter 4

## Classifying strategies - a Support Vector Machine approach

### 4.1 Support Vector Machines

There are many, many papers written about Support Vector Machines (SVM) and describing it in great mathematical detail (Bennet & Campbell, 2000; Boutell et al, 2004; Chang & Lin, 2012; Guggenberger; Burges, 1998; Fleury et al, 2010; Gunn, 1998; Hoffman 2010; Hsu et al, 2010; Mller et al, 2001; Vapnik, 2010). This paper will thus not be a regurgitation of the content of all these papers; it will limit itself to describing the main features of the SVM approach. A simplified and shortened version of Burge's (1998) tutorial on the subject will be used.

Support Vector Machines were developed from the research surrounding learning machines, a research field that gained traction in the 60:ies. Research on learning problems truly started in the 1960:s by Rosenblatt, with his Perception model (Vapnik, 2010). Around this time, Vapnik and colleagues suggested another algorithm, called generalized portrait (Smola Schlkopf, 2003). Much has happened since then in the field of both applied and theoretical learning problem / algorithm research. The Support Vector algorithm used in this paper is a nonlinear generalization of Vapnik and colleagues' algorithm. Since the 60:ies, Vapnik and Chervonenkis have gradually refined what they call VC theory, the framework surrounding their concept of statistical learning theory.

The Support Vector Machine (SVM) methodology was originally developed to solve binary classification problems (Hsu & Lin, 2002), but the method can be used on regression and linear operator inversion as well. The main concept behind the classification process is to divide the data into two, and use the first sub-sample to train the SVM and the latter for testing purposes.

The generalization achieved using SVM depends on the accuracy one wishes to achieve and the amount of error in the learning of a training set one can live with; the ability of the machine to learn a training set is called the machine's capacity.

What is meant by accuracy in this setting? The accuracy of the classification is defined as

$$Accuracy = \frac{\#correctly\ predicted\ data}{\#total\ testing\ data} \quad (4.1)$$

What does capacity mean? Burges (1998) gives a colorful explanation: "A machine with too much capacity is like a botanist with a photographic memory who, when presented with a new tree, concludes that it is not a tree because it has a different number of leaves from anything she has seen before; a machine with too little capacity is like the botanist's lazy brother, who declares that if it is green, it's a tree. Neither can generalize well." That, in a nutshell, is a learning machine's capacity. For a level of accuracy, a level of capacity is attained and there will be a trade off between how accurate and error-free your results will get using the SVM method.

To better understand what a learning machine is, we start by giving an example using our returns and strategies. Imagine we have  $l$  months of observations, and each observation consist of a pair of vectors,  $\mathbf{x}_i \in \mathbf{R}^n, i = 1, 2, \dots, l$  consisting of the returns we have and a vector  $\mathbf{y}_i$  with the strategies specified by the managers.  $y_i$  is called the "true" values, the values we "know" are correct, or wish to test if they are correct.

In our example, we start with only one strategy to keep things simple; a manager can be either trend following or not, and  $y_i$  will only take the values 1 if the program uses the trend following strategy and -1 otherwise. The data is assumed to have a distribution which is unknown to us. The point of the exercise is to let the SVM learn the mapping  $\mathbf{x}_i \mapsto y_i$ , i.e. how the returns

are connected to the strategy, or in SVM terminology, how the features are connected to the class.

The SVM machine can be explained by several mappings in-fact, as  $\mathbf{x}_i \mapsto f(\mathbf{x}, \alpha)$ , and for every given choice of  $\alpha$  a "trained set" is obtained as an output. Note that the machine is deterministic, i.e. for every given set of  $\mathbf{x}_i$  and  $\alpha$  the machine will always yield the same function output  $f(\mathbf{x}, \alpha)$ . To clarify, what is called a "learning machine" is in fact the family of functions  $f(\mathbf{x}, \alpha)$ .

With a particular choice of  $\alpha$ , we get the test error, the risk

$$R(\alpha) = \int \frac{1}{2} |y - f(\mathbf{x}, \alpha)| dP(\mathbf{x}, y) \quad (4.2)$$

where  $P(\mathbf{x}, y)$  is the distribution from which the data is drawn and  $\frac{1}{2} |y - f(\mathbf{x}, \alpha)|$  is called the "loss". This risk is connected to the capacity described above via the non-negative integer  $h$ , the so called Vapnik Chervonenkis (VC) dimension. The exact relationship between the risk and the VC dimension is given by

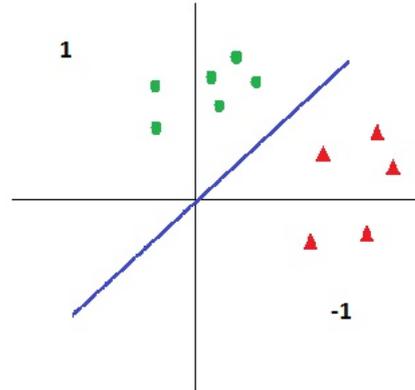
$$R(\alpha) \leq R_{emp}(\alpha) + \sqrt{\left( \frac{h(\log(2l/h) + 1) - \log(\eta/4)}{l} \right)} \quad (4.3)$$

which holds with the probability  $1 - \eta$ , where  $0 \leq \eta \leq 1$  is the limits of the probability and  $R_{emp}(\alpha)$  is the empirical risk given by

$$R_{emp}(\alpha) = \frac{1}{2l} \sum_{i=1}^l |y_i - f(\mathbf{x}_i, \alpha)|. \quad (4.4)$$

Using learning machines that yield an empirical risk of zero, one wishes to choose learning machines that minimize the VC dimension  $h$ . The equation above is independent of the distribution  $P(\mathbf{x}, y)$  of the data; we only assume that the data is independantly drawn from some  $P(\mathbf{x}, y)$ , but we do not know which distribution it is.

In our example, we are classifying only one strategy, i.e. the data can be either trend following or non-trend following. We will thus only consider the



**Figure 4.1:** The hyperplane; see the red triangles as trend-following strategies (-1), and the green circles as non-trend followers (1).

learning machines (functions)  $f(\mathbf{x}_i, a) \in \{1, -1\} \forall \mathbf{x}, a$ . We assume that our data exists on the space  $\mathbf{R}^2$  and that the set  $\{f(\alpha)\}$  consists of straight lines dividing the data into two sides, one where the data is classified as 1 and -1 in at the other side of the line (see Figure 4.1).

The points described above can be found in a space where data is separated by a hyperplane. Mathematically, a hyperplane is defined as

$$H(\mathbf{w}, b) = | \mathbf{w}^T * x + b = 0 \quad (4.5)$$

where  $\mathbf{w}$  is a weight vector and normal to the hyperplane and  $b$  is a variable indicating bias.

More formally, we use the unique representation

$$\min | \mathbf{w}^T * x + b = 1 \quad (4.6)$$

The distance between a point in the higher dimensional feature space and the hyperplane is

$$d(x, H(\mathbf{w}, b)) = \frac{\mathbf{w}^T * x + b}{\| \mathbf{w} \|} \quad (4.7)$$

To focus on when using SVM are the points nearest the hyperplane; the nearest points, to both sides of the hyperplane, are categorized into vectors. These vectors are called support vectors, and our goal when using the SVM method is to maximize the distance between a point and the hyperplane, i.e. minimize  $d$ .

As an example, we define support vectors for two points,  $(x_1, 1)$  and  $(x_2, -1)$

$$\begin{aligned} \mathbf{w}^T * x_1 + b &= 1 \\ \mathbf{w}^T * x_2 + b &= -1 \end{aligned} \quad (4.8)$$

We can now define our maximization problem as

$$\begin{aligned} \max \frac{\mathbf{w}^T * x_1 + b = 1}{\|\mathbf{w}\|} \text{ and } \frac{\mathbf{w}^T * x_2 + b = -1}{\|\mathbf{w}\|} \\ \frac{\mathbf{w}^T * (x_1 + x_2)}{\|\mathbf{w}\|} = \frac{2}{\|\mathbf{w}\|} \end{aligned} \quad (4.9)$$

As the maximization  $\frac{2}{\|\mathbf{w}\|}$  is equivalent to minimizing  $\frac{\|\mathbf{w}\|}{2}$ , we can re-write the maximization problem into

$$\begin{aligned} \min \frac{\|\mathbf{w}\|^2}{2} \\ \text{s.t. } y_i(\mathbf{w}^T x_i + b) > 1 \text{ for } i = 1, 2, \dots, n \end{aligned} \quad (4.10)$$

Such a function can be solved using Lagrangian multipliers. To incorporate Lagrangian multipliers, we re-write the problem as

$$L(w, b, \alpha) = \frac{1}{2} * \|\mathbf{w}\|^2 - \sum_{t=1}^n \alpha_t (y_t(\mathbf{w}^T x_t + b) - 1) \quad (4.11)$$

where  $\alpha_i$  is maximized and  $b$  and  $\mathbf{w}$  are minimized. We have thus changed our original constraints to those of the Lagrangian, which is easier to solve. Furthermore, we have moved to solving a problem involving the training set being in the form of dot-products which will allow us to solve non-linear problems.

When an SVM has been trained, we determine on which side of the decision boundary the test pattern  $\mathbf{x}$  lies and assign the corresponding class label to it.

The model might fail to find a hyperplane however. What does one do then? A solution is to allow a certain margin of error, introducing parameters  $C$  and  $s_i, i = 1, 2, \dots, l$ . Here,  $s_i$  is a set of positive variables (in optimization theory called positive slack variables) and  $C$  is a hyperparameter controlling the influence of  $s_i$ . A higher  $C$  corresponds to higher penalty to errors.

The optimization equation is changed into

$$\begin{aligned} \min \quad & \| \mathbf{w} \|^2 + C \sum_{i=1} \xi_i \\ \text{s.t.} \quad & y_i(\mathbf{w}^T \mathbf{x}_i + b) > 1 - \xi_i \text{ for } i = 1, 2, \dots, n \end{aligned} \quad (4.12)$$

It is worth noting that the value one gives to the parameter  $C$  (as well as that of the kernel parameter) has an influence on the accuracy of the classification task. The only difference from the original case is that  $\alpha$  is given an upper bound  $C$ . The solution to be achieved is still

$$\mathbf{w} = \sum_{i=1}^{N_S} \alpha_i y_i \mathbf{x}_i \quad (4.13)$$

where  $N_S$  is the number of support vectors.

To generalize the method and use a non-linear version of the learning machines, we need to use a "trick" involving what is called kernel functions. The trick involves observing the fact that the form with which the data appears in the training program is in the form of dot-products  $\mathbf{x}_i \cdot \mathbf{x}_j$ , and mapping the dot-product into a Euclidean space (or a generalized version of it, the Hilbert space), say  $\Phi : \mathbf{R}^d \mapsto H$ . What is used in the training algorithm is thus the dot-product of the functions  $\Phi(\mathbf{x}_i) \cdot \Phi(\mathbf{x}_j)$  in the higher dimensional space  $H$ . The trick is achieved when we use a Kernel function,  $K(\mathbf{x}_i, \mathbf{x}_j) = \Phi(\mathbf{x}_i) \cdot \Phi(\mathbf{x}_j)$  which does not require us to know the  $\Phi$  function explicitly. There are several Kernel functions one can use, and for this paper we will be using the Radial Basis Function

$$K(\mathbf{x}_i, \mathbf{x}_j) = e^{-\|\mathbf{x}_i - \mathbf{x}_j\|^2 / 2\sigma^2} \quad (4.14)$$

The solution we will obtain will be a global one, as is the case with convex programming problems.

SVM can be used for both classification and regression purposes; for this paper, we will use the classification capabilities of the SVM in order

to check which strategies the analyzed CTA programs actually use (if they corresponds to the stated ones or not). The SVM type we will use is the C-SVM, pertaining to the use of the C parameter (Chang & Lin, 2001).



# Chapter 5

## Data and Methodology

### 5.1 Purpose and Delimitations

In any due diligence process, the investor(s) wish to have a fair idea of how a fund might behave in the future. As you will see in this chapter, different strategies exhibit differing return distribution structures. The tools available today for detecting misclassification in the due diligence process have been mainly qualitative ones (ex. looking at disclosure documents) or quantitative models which are not adapted to the returns exhibited by hedge funds.

The main purpose of this paper will be to analyze which strategies CTA programs actually use, compared to the one(s) stated as well as presenting an easy-to-use model for detecting misclassification. This analysis will be conducted using a classification Support Vector Machine approach.

The results obtained by SVM have in academia seldom been analyzed (as such articles mainly focus on comparing two learning algorithms), and particularity not in financial literature as to the best knowledge of this author. The analysis following the SVM classification is thus a tentative one, with no articles available to be used as a point of comfortable base or reference .

What is the relevancy of analyzing misclassification and style drift in a due diligence context? The strategy used by a manager will greatly affect the returns of that manager's program(s). If the manager deviates from that strategy, intentionally or not, such action can have a huge impact on the subsequent net return that someone invested with the manager will get. Helping to resolve the style drift and misclassification issue is thus a very important one.

The term CTA is mainly attached to a registration, and there are many funds who trade and use similar strategies as managed futures programs; those funds will be left out of the analysis as including them is not feasible to do in the time period designated for this paper. This paper thus delimits itself to analyze programs and firms who are registered CTA:s.

Furthermore, this paper will not look into fund of hedge funds managing CTA programs.

## 5.2 Data

CTA program returns were obtained via the IASG database; included in the database used are 637 live and 422 defunct programs, spanning a time frame from 1977 to the date when the database was accessed, August 2012. Including the defunct programs alleviates the survivorship bias problem, found in papers analyzing the returns of CTA programs (Irwin, 1994; Fung & Hsieh, 1997). Not including funds that have stopped existing will lead to the returns analyzed to be "overly positive", as it is the only successful funds which would be included in the analysis otherwise. The returns reported in the database are monthly, thus limiting any attempts at analyzing daily data.

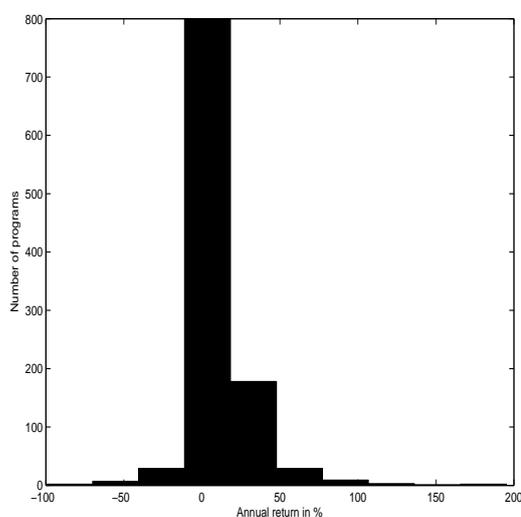
The programs in the IASG database are divided into self-reported strategies. It is worth noting that certain programs have not reported which strategy they use to IASG. Table 5.1 contains summary statistics for the data.

**Table 5.1: CTA program database descriptive statistics.**

The table below reports time-series averages based on cross-sectional information for programs in the period January 1977 to August 2012. Mean age is reported in years.

	# of programs	Mean age	Mean AUM	Mean return
All programs	1059	5.69	44.77 MUSD	11.58%
Active programs	637	6.43	59.97 MUSD	9.66%
Defunct programs	422	4.57	21.83 MUSD	14.48%

The data contains 1059 programs with an average asset under management (AUM) of 44.77 MUSD, 11.58% in annualized net of fees return and 5.69 years in average age, based on data obtained in August 2012. When looking at program age, one needs to keep in mind the relatively young age of the managed futures niche, and the rate with which it has grown; as stated



**Figure 5.1: Annual returns of active programs**

in the introduction, the CTA niche has grown by 151.8% since 2005. This is to be compared with the situation in 1979, when only one managed futures fund had available return data (Elton et al, 1987).

39.8% of the database consists of defunct programs, which makes it interesting from a survivorship bias point of view; academia focusing on hedge funds and mutual funds has a large issue with survivorship bias, a problem widely acknowledged (Brown et al 1992; Carhart 1997; Irwin 1994; Fung & Hsieh 2000). Brown et al (1992) show how the exclusion of defunct programs leads to the appearance of return predictability when evaluating funds. To quote Brown et al (1992, p.559): "The problems of interpretation caused by the ex post definition of winners and losers suggests that the results may also be sensitive to the most obvious source of ex post conditioning: survival".

When a program is added to IASG, the manager(s) of a program can choose to assign none, one or several strategies to it. There are 13 strategies to choose from in IASG (see Table 5.2).

Table 5.2: Strategies reported

Summary statistics. Strategies used, as reported by the CTA programs to IASG.com. The mean program age is shown in years, and the return, std. deviation, semi-standard deviation are mean values.

Strategy	# of firms	Ann. RoR	Prog. age	Std. dev.	Semi-std. dev.	Sortino ratio	Sharpe ratio	Skew	Kurtosis
Arbitrage	41	19.13%	3.36	4.58 %	4.37 %	2.30	1.78	1.30	7.85
Counte-trend (i.e. contrarian)	216	11.16%	5.19	4.97 %	4.97 %	0.74	0.70	2.92	19.70
Fundamental	163	12.17%	5.07	5.68 %	5.30 %	0.92	0.80	1.40	9.71
Momentum	83	10.31%	4.11	4.31 %	4.28 %	0.75	0.63	4.11	23.93
Option purchasing	48	16.84%	3.13	6.76 %	6.26 %	1.20	1.17	0.76	5.98
Option spreads	68	13.97%	2.75	6.49 %	5.90 %	1.13	1.14	0.67	4.78
Option writing	99	17.30%	3.45	6.54 %	5.76 %	1.39	1.21	1.24	7.41
Pattern recognition	83	12.48%	4.20	5.54 %	5.40 %	0.80	0.72	3.01	16.01
Seasonal/cyclical	31	14.49%	4.94	4.54 %	4.35 %	0.79	0.77	2.06	9.02
Spreading/hedging	55	13.84%	3.62	5.59 %	5.82 %	0.84	0.92	0.03	3.06
Technical	141	13.79%	4.10	5.89 %	5.75 %	0.92	0.79	3.24	22.04
Trend-following	389	10.78%	6.25	5.67 %	5.57 %	0.55	0.56	2.73	19.78
Other	127	8.01%	5.11	5.32 %	5.00 %	0.56	0.55	-2.05	15.53

The strategy with the highest mean age is the trend-following strategy, while the one with the lowest mean age is the option spreads strategy. In all, the option strategies along with the arbitrage strategy show the lowest mean age. One explanation can be the inherent vulnerability to event risk which is built into option strategies. Such strategies seem to show stellar returns until an event appears after 2-3 years and ends the program. The remaining strategies seem to exhibit similar mean age and returns amongst themselves. The strategy with the highest mean annual rate of return (RoR) is the arbitrage strategy; as stated earlier, this is also one of the strategies with the lowest mean age. Interestingly, the arbitrage is also the strategy with the highest Sortino ratio and a relatively low semi-variance, further stressing the need to look to other aspects other than the traditional ratios (ex. mean age) to assess risk.

The distributions of the data are shown in figure 5.2 and 5.3. The arbitrage strategy shows a thick right tail and positive skewness. It would also appear that the arbitrage strategy exhibits a low survival rate (shown by a low mean age), along with the options strategies.

The option strategies, the option spreads in particular, exhibit left tails which are more worrisome (i.e. the inclusion of extreme negative events) than the other strategies. A similar distributional structure is exhibited by the seasonal/cyclical and spreading/hedging strategies.

The trend-following strategy exhibits kurtosis and skewness values similar to those of the counter-trend strategy, though trend-following funds exhibit a larger mean age.

Interestingly, the funds who chose to classify their strategy as "Other" are the only ones to show a negative skewness. One reason for their reluctance to disclose a specific strategy can be that in general they perform less well than their peers (as the "Other" category shows the lowest mean RoR).

### 5.3 Results of the SVM classification

The SVM method uses terminology which might feel foreign for a finance practitioner, the non-mathematician or someone who is not familiar with learning algorithms in general. Variables are in this context called features, and our strategies will be designed as classes. The features used in this pa-

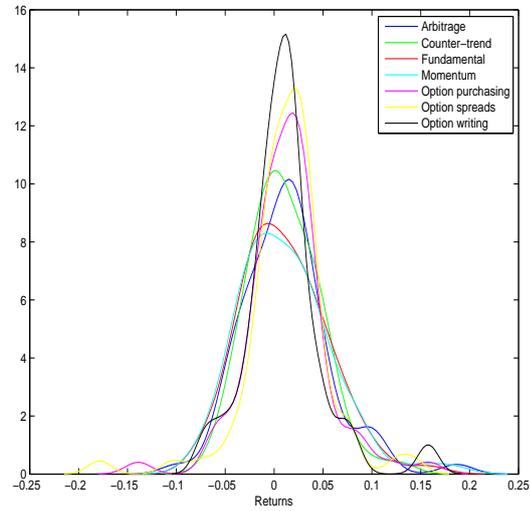


Figure 5.2: (a) Distributions of the programs using strategy 1 to 7.

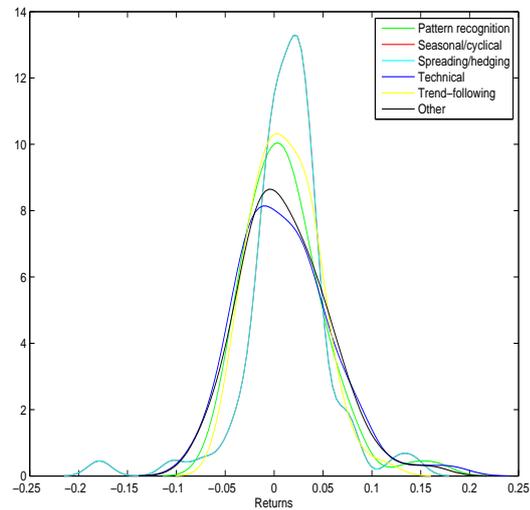


Figure 5.3: (b) Distributions of the programs using strategy 8 to 13.

per, what is most related to the classes (i.e. strategies) is the returns of the programs.

To analyze the data, the same time period needs to be used. In a trade-off between period length and available CTA programs (i.e. data points), the time period January 2006 - January 2012 is used, and the number of programs used in the analysis thus become 387.

It is also worth noting that only the programs with a designated strategy were included (i.e. the "no-strategy" programs are excluded from the analysis).

The parameters  $\gamma$  and  $C$ , the kernel and SVM parameters we need to specify, are arbitrarily chosen as the values of 1 and 10 respectively.

As we use programs who may have more than one strategy (i.e. they are multi-class in nature), the cross-training method as described by Boutell et al (2004) is used. Furthermore, the data was normalized using the respective return series' standard deviation.

Now, a small mini-tutorial on how SVM is to be implemented is in place, for those wishing to do similar analysis, and in order to understand the results better. One can program an SVM and kernels oneself, or use toolkits created by those who master the subject better. For this paper, the LIBSVM MATLAB toolkit was used (which can, at the moment, be downloaded for free from [www.csie.ntu.edu.tw/~cjlin/libsvm](http://www.csie.ntu.edu.tw/~cjlin/libsvm)). To understand more about the LIBSVM tool-kit, the reader is referred to Chang and Lin's (2001, last updated 4 April 2012) work on the subject. The SVM types supported by LIBSVM are quadratic minimization problems; for those wishing to try out a linear SVM, other tools need to be used.

The strategies were used as classes, in a an  $m$  by 1 vector looking something like  $X = [x_1 \ x_2 \ x_3 \ \dots \ x_{13}]$ , and the returns of the programs were used as features in the  $m$  by  $n$  matrix. If the database used is very large, it needs to be sparsed before use which is quite simple using the MATLAB function *sparse()*. The author of this paper is available to answer any questions you may have regarding the implementation process.

To the result of the classification performed using SVM; how are the programs actually classified? Which are the true strategies used? In Table 5.3 you can see the result of the classification, which had an accuracy of 57.0%

(which is defined as the number of correctly predicted data divided by the number of total testing data). Table 5.1 contains summary statistics for the data.

**Table 5.3: SVM classification result**

How the CTA programs fared; what they did, and what they say they did. The "SVM classification" column shows the number of strategies funds per strategies (in %) as labeled by SVM. The column "Stated" column indicates the number of funds per strategy (in %) as stated by the managers of the funds.

Strategy	SVM classification (%)	Stated (%)
Arbitrage	0.32%	0.96%
Counter trend (i.e. contrarian)	7.96%	16.24%
Fundamental	8.92%	9.24%
Momentum	0.32%	5.10%
Option purchasing	0%	1.27%
Option spreads	0.64%	1.59%
Option writing	3.50%	3.18%
Pattern recognition	0%	4.78%
Seasonal/cyclical	0%	1.59%
Spreading/hedging	0.64%	1.59%
Technical	1.27%	5.41%
Trend-following	72.3%	39.17%
Other	4.14%	9.87%

We need to address the weakness of these results before analyzing the data further. For one, the accuracy of the result is 57%; there is always a trade-off between over-fitting and allowing for uncertainties in the result. Furthermore, when we work with multi-class labels in a data set where data is not easily separated and certain classes with small sub-samples are used, accuracy is affected.

The result analysis is illustrated by choosing five programs in the data at random. We look at their stated strategies and then compare them to the predicted ones (see Table 5.4). We also read the specifications of the funds analyzed in the example, regarding the details of the strategies used.

The only deviating information about the funds analyzed above comes from fund #5, which does mention the use of trends when trading. The way

**Table 5.4: Example: how 5 specific programs fared**

The ID:s of the programs are used to map the stated strategy to the predicted one. As to not single out any specific managers or firms, the names of the programs are not stated.

Program #	Stated strategy	SVM classification
1	Trend-following	Trend-following
2	Trend-following	Trend-following
3	Fundamental	Trend-following
4	Option writing	Trend-following
5	Technical	Trend-following

one is to understand the result in the example is that given the accuracy of the model and trying to balance the problem of over- and under-fitting, the SVM classification presents strategies (labels if you will) where program returns and original labels are connected to new labels. The strategies presented by SVM are the result of the optimization problem presented in the preceding chapter. Basically, the SVM will show you the patterns it has found based on the parameters, features and classes given.

Now we move back to analyzing our data, as see in Table 5.3 above. Though only 39.17% of the funds stated they use a trend-following strategy, the SVM analysis classifies 72.3% of the funds as trend-following; such figures are more in-line with what has been assumed by practitioners (i.e. that the majority of CTA:s are actually trend-followers). The two strategies that SVM re-classified the most, second to the trend-following strategy, appears to be the counter-trend and Other strategies. The rest of the strategies show no large changes in their classifications.

What makes funds managers classify their funds wrongly? Certain strategies come in and out of style, and certain strategies attract more capital than others at different times, alas, as certain investors may look less to the strategy with the desired return distribution profile and more to which strategy is in vogue. Misclassification can also be un-intentional as explained earlier in the paper, due to trading actions that lead to style drift. It can also be a strategy in itself, to apply such dynamic trading that shifts strategy depending on the market situation.

## 5.4 Conclusions

In this paper, we have used the SVM for classifying strategies, an exiting way of automating part of the due diligence process. The SVM method can be used for other parts of an investor or manager's work however; the possibilities are endless, as it where.

Research is being done on kernel functions, which parameters to use for SVM, the use of multi-class SVM and many of the aspects of this exiting method. This paper does not intend to evangelize around the use of the SVM method, but to present the reader with a new way of thinking when challenged with the due diligence process of choosing a CTA manager, and for CTA managers when conducting risk management.

Though one should not generalize with the accuracy given (or any accuracy, as a 100% rate is a sure sign of over-fitting), the results obtained show that managers do not always "plays as they say", i.e. the strategies stated are not always the one(s) used. As strategies can have a large effect on the net returns obtained by investors, this opens up the question of how investors are to address the problem of asymmetric information when dealing with managers. The automation of the strategy classification will hopefully help along the way.

As stated before, such an automation process may very well be used in other areas of investors' and managers' work. Another interesting topic to look into, would be to analyze the strategies managers use during different market regimes.

The analysis itself takes a few seconds, minutes if one includes setting up the proper toolkit. Yet, using SVM we have in a powerful way re-classified the strategies of funds as compared to the ones given in their disclosure documents. This is but one tool to look at when conducting due diligence, but it is an important step in automating the process.

# Appendix A

## Commodity Trade Advisors (CTA:s) and Managed Futures

### A.1 What is a CTA? What is Managed Futures?

To write a thesis relating to Commodity Trade Advisors (CTA) and managed futures - used interchangeably in this paper - one needs to start by defining what these terms mean. One also needs an explanation of how the futures market works. This part can easily be skipped if you are already familiar with the CTA / Managed futures niche.

An important aspect of futures is the need to renew them when they expire; a future is after all a standardized contract with a certain life span, or expiration as it is called, of around a quarter of a year or a month. The renewal of a futures contract is called a "roll". Such a "roll" can have an effect on the returns of a managed futures program; this can be an important aspect to keep in mind, when evaluating the transaction costs of CTA:s and the problems they might have with these costs (Burghart, 2010).

A CTA is a manager who provides investors with advice for trading futures contracts as well as other instruments such as interest rates and currencies; a CTA manager or a fund of fund dealing with CTA managers can also trade on the behalf of the investor, using managed accounts. A managed account is an account owned by the investor, but managed entirely by the CTA manager. Simply put a CTA manager invests money on the behalf of one or several investors, based on one or several strategies, and one or several models.

CTA managers are required to register themselves with the Commodity Futures Trading Commission (CFTC), and become a member of the National Futures Association (NFA). The NFA's activities are overseen by the CFTC. Both of these organizations are based and operate in the USA. It's important to note that while the CFTC is a governmental body, the NFA is a private self-regulatory organization. An investor wishing to know more about a CTA firm can do so via NFA, using the CTA firm's NFA ID or firm name.

Managed futures funds only make up a small part of the capital markets (Till & Eagleeye, 2011); of the 55 trillion global capital markets, CTA funds make up 0.05%.

What constitutes a CTA is not always clear, and definitions might differ in Europe, the US and in Asia. The main CTA attribute is thus the CTA registration with the NFA and the CFTC.

What generally differs Hedge Funds from managed futures is that the latter mainly trades futures contracts. Managed futures are simply a sub-category of Hedge Funds, a Hedge Fund strategy.

Trading mainly in the futures market, managed futures programs are generally very liquid. Futures contracts require a low margin with which to short sell futures, offering a leverage opportunity without borrowing money. The low margin requirement has been brought up as a problem by some investors, who do not wish to be subjected to too much leverage risk. Problem or no, it all boils down to risk management, and leverage is a necessary and wanted part of futures trading. Another distinctive attribute is that managed futures are mainly active, and not passive, in their trading.

Compensation wise, a CTA manager receives a management fee and an incentive fee (also called performance fee) which is usually paid out only if the program generates a return above a certain high water mark. A high watermark is the previous period's peak followed by a loss; practically, this insures that the manager does not receive additional compensation if s/he have performed badly.

Generally, the usual fee structure is 2/20, i.e. a fixed management fee of 2% and a conditional incentive fee of 20%. There is a debate surrounding which fee structure is optimal in order for the CTA managers to perform optimally.

## **A.2 Organizational structure of CTA managers**

A managed futures program is run by one or several Commodity Trade Advisors (CTA). CTA:s are generally organized the same way Hedge Funds are; the managers of the CTA fund are general partners, whilst investors enter as limited partners.

CTA:s have been criticized for being too opaque. As Hedge Funds do not deal with the general public (only wealthy private investors and large institutions), they do not fall under the strict legislative jurisdiction of the countries where they are based, ex. the SEC (Securities Exchange Commission) in the US or Finansinspektionen in Sweden.

Non-disclosure of managers programs is also tied to the perceived skill and added value provided by the managers' models. Divulging such models might to some managers be perceived as detrimental, while non-disclosure might deter certain investors from investing in managed futures programs. The need for secrecy by managers, and the need for more information by investors, creates a conflict which might be hard to overcome. That is where good risk management and good due diligence comes in.

## **A.3 Due Diligence by investors: evaluating managed futures programs**

Before choosing to invest with a manager and a certain managed futures program, investors do (hopefully, and preferably) a thorough qualitative as well as quantitative analysis of the managers running the program as well as the program itself.

The process of evaluating a CTA program is called due diligence. A due diligence includes qualitative as well as quantitative steps, which combined will lead to a business decision: to invest or not to invest.

In this section, we will look at the qualitative and quantitative aspects of the due diligence performed (or should be performed) by investors when choosing one or several CTA managers and programs to invest in.

### A.3.1 Qualitative aspects

A first step in the qualitative part of the due diligence is to do a background check on the CTA manager and firm (all principals involved) of interest. One of multiple steps that can be done when conducting a background check is via the National Futures Association (NFA); such a check can be done on-line on their website or via phone. One only needs the firm's name to do such a check.

A second step is looking through the CTA firm's disclosure document; though a lot of information about a CTA program can be found in a manager's disclosure document, such a document is in no way an exhaustive basis for taking a business decision to invest. It is however a good starting point. A disclosure document should be updated every ninth month at the very least; an older document should be viewed with caution.

In general, a managed futures fund will have its orders cleared and executed via a Futures Clearing Merchant (FCM). According to investopedia.com, an FCM is a merchant involved in the solicitation or acceptance of commodity orders for future delivery of commodities related to the futures contract market. Such a merchant can also extend credit to the clients. As part of such a relationship, certain merchants offer CTA:s commission fees for using their services; this is a situation that might lead to a conflict of interest. The chosen merchant might take higher transaction cost fees than necessary; the manager wins, but the investor is left with less gross returns.

How long the CTA firm has been active is an indicator that usually comes up in a due diligence. One interviewed investor has a requirement of minimum 10 years of experience by a firm before trading with them, while another investor specified 2 to 3 years as a minimum. The reason given was that a firm which has been around for a longer period has experienced different cycles, recessions as well as expansions. As previous returns are no indicators of future ones, one need to analyze fund age with caution. A manager who has only been around for 2 years might very well perform much better long term than a manager who has been around for 20 years.

Looking at specific periods, which in theory should have been favorable for a certain CTA strategy and program and has been favorable for peers with similar strategies, is an interesting parameter to include in the analysis; ex. during a trending month, the returns of trend following CTA:s should be positive. If a trend following program consequently performs badly during trending periods, that would constitute a bad sign. As mentioned above;

previous returns prove nothing.

A tactic used by investors has been to buy CTA managers when they are experiencing a draw-down. If other indicators indicate that the program, its risk management, the manager and the firm is sound, a draw-down is quite a natural state to be in for CTA programs. Seeing as the return profile of CTA programs are leptocurtic (positively skewed and exhibiting "fat tails"), they are expected to have several small losses and few but large, profits. That would be the "expected" profile, given a trend following strategy and being invested in a liquid market, but it is not to be assumed that all CTA programs exhibit the same return profiles (i.e. distributions).

There are articles written on the fund size aspect alone; this paper will confine itself in discussing the minimum and maximum fund sizes to look for in general. As one manager specified, a fund over 5 billion USD might start feeling the effects of liquidity becoming an issue; if a fund is too large, its possibility to enter trades becomes fewer. For a fund which is too small, the risk of being too dependent on one or few investor can become an issue. Furthermore, transaction costs and deal sizes may also be a constricting factor.

A program needs to go through continuous improvement to be viable; a program running on the exact same methodology for a very long period of time will not be a winning one; markets change continuously. Having a dedicated research team is thus a good indicator.

One investor mentions the use of questionnaires; he would give managers a questionnaire containing one risk question rephrased in eight different ways. The investor believes that a manager who has thought through a risk management mechanism would answer all the different questions in a similar manner. The use of questionnaires is common, though no research has been done on their efficiency when selecting CTA managers.

Understanding the risk management used by a CTA firm and its program(s) is thus a paramount aspect of the due diligence process. Risk involves many aspects; operational, strategy, model, implementation, service provider risk and conflict of interests and certainly more factors which are not listed here depending on a particular investor's situation.

### A.3.2 Quantitative aspects

The first quantitative measure many an investor look for when evaluating a CTA manager is the maximum draw-down, which is the cumulative largest decline of the CTA program. All CTA:s go through a draw-down; the important question to ask oneself is how much and for how long (for more information about draw-down and maximum draw-down, please consult the Risk Management section). In general, a draw-down is perceived by the market to be normal, while investors perceive it as a sign of weakness. Why any of them is correct, and on what grounds, is an important question to ask oneself, and the answer should not be "experience tells me that ...".

Though it has been said to death that past returns are not indicative of future ones, looking at annualized return is a favorite hobby of many. A better measure for the investor looking to benchmark past returns would be the risk-adjusted annualized or monthly return. Such a measure is obtained by dividing the return (with the frequency of choice) with the semi-variance (i.e. negative std. deviation) of the program; this measure is called the Sortino ratio. A CTA program can have stellar positive returns, which were obtained at substantial risk; for risk-averse investors seeking to invest with such a risk taking manager, this is cause of concern.

Newedge (2003 April 17) argues that daily data provides a better insight into a manager's volatility as compared to using monthly or annual data. The authors found that the volatility estimates obtained using monthly data are around 4.6 times wider than the ones obtained using daily data. What the authors also note, quite correctly, is that daily data is afflicted with more noise than monthly data. The frequency of the data available will thus affect the measures used in the due diligence process.

The horizon and strategy used by a CTA manager has been found to affect performance (Szakmary et al, 2010). Agarwal and Naik (2000) also find a connection between time horizon, yet no relation between strategy and performance. Academic literature diverges when it comes to conclusions relating to the impact of strategies and horizons of hedge funds on performance.

We finish off the quantitative due diligence section with bringing up the subject of misclassification and the risk of managers stating the use of one strategy when in fact another one is in use; the interested reader is advised to read Chapter 2 regarding the subject.

## A.4 CTA managers' Risk Management

Rather than focusing on optimizing returns, CTA managers are (or should be) more concerned about the risk level of their trading; risk management is thus a vital part of any managed futures program. The model used to trade may be very simple (and should be, if one is a fan of the Occam's razor concept), but the risk management mechanism should be very well thought out.

As investors can choose managers on the basis of certain target volatility, this parameter is not the focus of risk management. The parameters discussed in this paper are in no way exhaustive, nor are they used by all CTA managers.

### A.4.1 Risk Measures

Many are they, who use traditional risk and performance measures that hinge on assumptions not in line with the risk and performance profile of CTA programs.

The Sharpe ratio, variance and standard deviation are salient examples; these measures rest on the assumption of normality in the returns and volatility of returns. For CTA programs, it is widely known that returns exhibit fat tails (i.e. non-normal distributions), autocorrelation and returns that may be positive mainly during certain market conditions. Furthermore, the standard deviation concept hinges on the assumption that investors dislike positive risk to the same extent as negative risk; one can assume that an investor, seeking positive returns, would view positive risk as benign. Yet, alas, the Sharpe ratio is still used by investors and CTA managers alike, when communicating and in the due diligence processes. Alternative measures need to be presented.

### A.4.2 Semi-variance and semi-deviation

Though standard deviation and variance are the most common risk measures in the world of finance, they have flaws which make them inappropriate to use when evaluating managed futures programs. Firstly, standard deviation takes into account both negative and positive deviations. As an investor however, positive deviations are beneficial for you. Secondly, standard deviation are based on a normality assumption regarding returns; as managed futures program returns usually show positive skewness and kurtosis, the normality

assumption is not valid.

Semi-variance and semi-standard deviation only includes the values below the mean, i.e. negative variance and negative standard deviation:

$$\text{Semi - variance} = \frac{1}{n} * \sum_{x_i < \text{mean return}}^n (\text{Mean return} - x_i)^2 \quad (\text{A.1})$$

$$\text{Semi - standard deviation} = \sqrt{\text{Semi - variance}} \quad (\text{A.2})$$

where  $n$  is the total observations below the mean, and  $x_i$  is an observation less than the mean.

### A.4.3 Drawdown

Draw-down takes into consideration the accumulated losses over time, i.e. it is a multi-period risk measure.

A draw-down is a period of negative positions; basically, it is the percentage change in net asset value between a high peak and a subsequent trough. For a program to be in a draw-down is not unusual and not necessarily a sign of distress. Such draw-down is tightly connected to the fact that markets are not always trending (and most programs are trend following in nature), and managed futures programs in general are supposed to generate positive returns mainly during such periods. When the market is ranging, which is 60-65% of the time (Andrew Abraham, interview 2012-07-25), managed futures programs will most likely go through a draw-down. Thus, a managed futures program using a trend following strategy showing red is going to be the case more than 50% of the time. Due to its multi-period characteristic, it would be interesting to use draw-down in evaluative purposes, even though previous research question analysis based on historical data (Acar & James, 1997) and using draw-down data in particular (Elaut et al, 2011).

### A.4.4 Maximum Drawdown

As the name indicates, maximum draw-down is the worst draw-down a manager has experienced since a specified period of time (most commonly, since inception).

To properly calculate the Maximum Draw-down measure, corrections should be made to account for track length, frequency of measurement and volatility of the asset (Hardin et al).

#### A.4.5 Omega ratio

Omega,  $\Omega(r)$ , is the ratio of the probability of gains relative to the probability of losses, for a given level of risk,  $r$ . Omega is calculated using historical returns, and does not use any pre-defined distribution, i.e. the distribution of the data is the one observed. What does this entail, in a practical sense? Since we do not assume a certain distribution, the data's own information regarding higher moments is used. As managed futures program returns can show quite differing levels of skewness and kurtosis for a given strategy, allowing for differing higher moments is quite important.

The Omega formula is given by

$$\Omega(r) = \frac{\int_b^r (1 - F(x))dx}{(\int_a^r F(x)dx)} \quad (\text{A.3})$$

The interval  $a$  to  $b$  is the return interval,  $F$  is the cumulative distribution of returns and  $r$  is the loss threshold. For a given level  $r$ , a higher Omega is preferred to a lower one (i.e. higher probability of gains than losses).

#### A.4.6 Calmar ratio

The Calmar ratio was developed as an alternative to the Sharpe ratio, a measure which is evidently flawed when evaluating managed futures which have non-normal distributions.

The Calmar ratio is used to evaluate a return from one period against the maximum draw-down the program has experienced during that specified period.

$$\text{Calmar ratio}_t = (\text{Annualized return}_t) / (\text{Maximum draw - down}_t) \quad (\text{A.4})$$

A high Calmar ratio indicates that for a given annual return, the manager had attained a low draw-down. This measure can be misleading as a risk indicator, if not used properly. The Calmar ratio should be used when benchmarking CTA:s with very similar programs against each other, as it then can be assumed that they should have suffered similar draw-downs if they run similar programs. In a setting where the draw-down can be assumed to be the same for all investigated managers, the Calmar ratio may be used as a risk measure.

### A.4.7 Sortino

The Sortino ratio is also an alternative to (or enhanced version, if you will) of the Sharpe ratio, where only the negative standard deviation is accounted for when relating it to returns. As positive standard deviation means positive returns to the investor, including such risk in a risk measure does not make any sense. Positive risk is thus removed from the Sharpe ratio, and the Sortino ratio is achieved:

$$\textit{Sortino ratio} = \frac{E(R) - T}{\sigma_{\textit{negative}}} \quad (\text{A.5})$$

where  $E(R)$  is the expected return,  $T$  is the target required return and  $\sigma_{\textit{negative}}$  is the target standard deviation of returns below the mean in the sample.

# Appendix B

## CTA/Managed Futures Categorization

A CTA program can have an investment style, i.e. decision making system, which is systematic, discretionary or a mix of both. As part of the investment style, a program can further trade short-, medium- or long-term. Furthermore, the manager can use one or several combinations of different trading strategies such as contrarian or trend-following for one or all programs under management. And lastly, a CTA manager can also trade in different markets, such as commodity or equity.

As a side note, certain investors categorize CTA managers in light of their fee compensation structure.

### B.1 Investment styles

#### B.1.1 Systematic versus Discretionary

Systematic models and trading techniques build on the psychological regularities of the markets; for trend following techniques in particular, these regularities are shown in the form of up- or down trends.

When stating that a model is systematic, it refers to the fact that rules defined *ex ante* decide entirely (or almost) which trades to be taken based on entry and exit signals given by the predefined rules of the model.

A non-systematic model is called discretionary, i.e. trading decisions relies solely on the managers judgment and discretion.

Certain programs use a mix of both investment styles; as an example, a fund might use systematic trading signals and discretion when choosing to invest or not. The extent to how mixed investment styles are can vary greatly among CTA programs.

### **B.1.2 Short-, medium and long-term trading horizons**

As part of a CTA:s trading strategy, a trading horizons is set. The choice of holding period is very important, as differing trading horizons give rise to differing return distributions.

There are as many definitions of short-, medium- and long-term trading horizons as there are CTA managers (and investors); the definitions given in this paper are general ones.

A short-term trading horizon ranges from high-frequency trading with a holding period of seconds up to hours, to a few weeks.

A medium-term trading horizon can vary from a month to three years. Long-term trading programs have holding periods that last from three years to a whole lifetime. As mentioned above, these definitions can be questioned, but give a crude definition.

## **B.2 Trading Strategies**

There are many strategies used by CTA:s, and it is a paper in itself to describe them all throughly. We will constrain ourselves with going through some of the strategies that will be analyzed in this paper.

Trend Following is quite often used synonymously with CTA:s. Most CTA managers use trend following strategies (Fung & Hsieh, 1999 who state 58% of CTA managers use Trend Following programs; Till & Eagleeye, 2011). Burghardt et al (2010) found a correlation of 0.97 between the returns of the Newedge CTA Index (comprising of an equal number of trend following and non-trend following programs) and the Newedge CTA Trend Sub-Index (comprising of the returns of CTA programs which are known in the market for being trend followers). Over the period 2000 -2009, Berghardt et al found 49% of the 196 CTA:s in the CTA Trend Sub-Index to be trend followers. The authors point out that it is difficult to build a portfolio which does not

exhibit trend following-like returns; a portfolio comprising of no trend followers produced in their study a return correlation between the portfolio and the Newdedge Trend Following Sub-Index of 0.60.

The trend following strategy as well as managed futures is said to have been pioneered by Richard Donchian, who started the first publicly traded commodity fund in 1949.

What explains a trend? James (2003) describes the phenomena as occurring due to long term economic pressures. A simple trading strategy can be implemented using a moving average indicator. Other models connected to trend following strategies would be moving average crossover and range breakouts (Abrams et al, CME Group; Burghardt, 2010). In its simplest form, the range breakout model takes on a parameter, and if the price of an asset falls/rises above a certain limit during a specified period (ex. 10 days), a sell or buy signal is generated. The moving averages crossover model works as it sounds; if two moving averages with different time periods cross each other (ex. one being over the other), a trading signal is generated.

Moving on to contrarian strategies; a contrarian trader trades on the belief that a mean reversion of returns will occur in the future. Or put more simply, a contrarian believes that investors in general are affected by herd behavior, which leads to mis-pricing of certain assets. A contrarian trader thus tries to find such mis-pricing, and buy an asset when it is distressed, and shorts assets which appear to be overpriced; i.e. a contrarian trades in the opposite direction of the prevailing market trend, thus leading to the strategy being at times termed as counter-trend. Yet another description of a contrarian strategy was given by Lo and MacKinlay (1990); selling past "winners" and buying past "losers". Such a strategy does imply the presence of negative auto-correlation and stock market overreaction, though certain authors argue that this need not be the sole explanation of contrarian strategy profits (Lo and MacKinlay, 1990; Conrad et al, 1997). Contrarian strategies have been shown to be profitable for a limited sub-period (1926-1947) when used for short-term holding periods such as weekly or monthly, and for very long trading horizons such as 3 to 5 years (Conrad & Kaul, 1998). As there is no research to indicate whether contrarian strategies are still profitable, the use of such a strategy should be questioned.

Momentum strategies can be seen as a form of trend following strategies, but one should make a distinction between the two; being similar does not mean they are identical, an important aspect often neglected. A momentum

strategy is based on the belief that past winners will continue to perform positively, while past losers will continue to perform badly. A momentum trade is done by first ranking the securities of interest, then taking long orders on the top performers and short orders on the bottom losers. Szakmary et al (2010) argue that one of the reasons why momentum strategies earn positive returns is due to the fact that they have both a cross-sectional and time series component. They further view momentum to be a security and not market wide phenomena. It is important to point out that the positive returns obtained by Szakmary et al were obtained using an intermediate horizon, and that the choice of horizons has an effect on the returns obtained.

Momentum strategies appear to perform well for medium-term holding periods, such as 3 to 12 months (Conrad & Kaul, 1998).

The general definition of arbitrage is the simultaneous sale and purchase of an asset, with the goal of making a profit on the difference between the sale and purchase price. This is achieved by buying and selling identical assets in different markets or differing formats. An issue that can arise when trying to achieve an arbitrage deal would be the differing trading hours of different markets, execution time and trading terms.

Arbitrage is commonly used in option valuation modeling (Figlewski, 1989). The assumptions surrounding arbitrage strategies in academia differ from those used by practitioners, and the difference between arbitrage as it is used theoretically and in real life is an important one, as pointed out by Figlewski. Theory makes assumptions about perfect markets, continuous instead of discretion re-balancing, no transaction costs and the use of historical volatility.

As contrarian strategies and trend following strategies are the different sides of the same coin, so are the fundamental and technical (also called "quant") strategies. Both technical and fundamental strategies can add value to a portfolio, J-P Morgan argues in an article on the subject (Mergentaler, JPMorgan Investment Analytics and Consulting), a point worth taking note of. Described simply, technical strategies use mathematical and statistical formulas to value assets, while fundamental strategies use accounting macro economic indicators to value assets. It is not uncommon to use a mix of these strategies, i.e. using a hybrid strategy of both fundamental and technical indicators when trading. Actually, it is common to mix between different kind of strategies overall, using for example a technical arbitrage strategy and a trend following one.

## B.3 Traded Markets and Assets

The name Commodity Trade Advisor can lead the reader to believe that CTA:s only trade with commodity features. Though this might have been true when the managed futures niche was in it's infancy, it is no longer the case. CTA:s trade, besides commodity futures, futures involving currencies, interest rates, equities, bonds and other securities (both directly and/or via futures). Certain CTA:s also include options in their trading. A CTA program can be limited to one country, continent or it can be global.

The composition of the programs analyzed in this paper, as defined by the database used (iasg.com), are:

- ◇ Currency futures
- ◇ Currency FX
- ◇ Industrial Metals
- ◇ Precous Metals
- ◇ Energy
- ◇ Grains
- ◇ Interest Rates
- ◇ Livestock
- ◇ Softs
- ◇ SSF (Single Stock Futures)
- ◇ Stock Indexes
- ◇ VIX
- ◇ Other

## B.4 Fee Strcuture

Generally, a CTA manager receives remuneration from investors in two forms:

1. Management fee and

## 2. Performance fee (incentive fee)

The most prevalent fee structure in the hedge funds industry, and the CTA sphere as well, is 2/20, i.e. a 2% management fee and a 20% performance fee (Bhardwaj et al 2008 found the most common fee structure to be 2.15/19.5).

The management fee is a fixed percentage point fee calculated based on the assets invested with the manager. The performance fee on the other hand, is based on the returns provided by the manager to the investor. Usually, such a fee is not paid out until the manager reaches over a certain level higher than the maximum negative decline the manager had attained during a certain elapsed period, say a quarter. Ex. if the manager was down 3% in first quarter, and up 5% the next, the manager only receives performance fees tied to the 2% rise above the negative level reached the quarter before. Such a level is called the high watermark (i.e. the manager needs to be above water, above zero in returns to receive a performance fee). Calculating an optimal fee structure for individual managers can be done by setting their target volatility in relation to a target return and a certain fee structure (ex. 2/20, 1/30).

The chosen fee structure can have a large impact on net returns; even though a manager generates positive gross returns, the positive return can get eroded if the fees are too large. Subsequently, if the fees are too small, the managers might be impaired in their work, and can face a large default risk.

# Appendix C

## Managed futures performance and predictability

### C.1 Distributions of Managed Futures Programs

The returns of managed futures program strategies do not exhibit a normal distribution (Szakmary et al, 2010, Fung & Hsieh 1999, Potters 1998). This is in no way surprising when you think about it; these programs exhibit positive returns during extreme, abnormal market situations. It stands to reason that managed futures programs will exhibit skewness and kurtosis which deviates from that of a normal distribution (Till & Eagleeye, 2011).

CTA strategies are also referred to, at times, as long volatility, which might be misleading; trends, for the programs following such a strategy, do not only appear during volatile markets.

### C.2 Performance of Managed Futures Programs

Fung & Hsieh (1999) note that one of the main reasons hedge funds and mutual funds have different return characteristics is due to the use of different trading strategies and investment styles. Szakmary et al (2010) also note that horizon and strategy design play an important role in the performance of a trend following strategy fund.

In a test of trend following strategy performance, Szakmary et al (2010)

found the strategies tested to yield positive results (after deducting transaction costs) in 22 of the 28 futures markets tested over a time span of 48 years. Not surprisingly, other authors find contradictory evidence, showing CTA:s to under-perform, yet persist as an asset class due to poor transparency (Bhardwaj et al, 2008).

Till & Eagleeye (2011) show that during each period when the S&P 500 has declined by more than 6% (since 1980), managed futures outperformed the S&P 500 by 17% on average.

An important factor to consider when evaluating managed futures performance is the auto-correlation of security prices used by trend following strategies; when auto-correlation decreases, so does performance (Kidd & Brorsen, 2004). This is quite intuitive, as autocorrelation among security prices is a strong indicator of trends.

Performance has been argued to differ between managers based on size and the track record of the manager (i.e. age of the program). Sawicki and Finn (2002) argue that smart money chases small funds, meaning that investors prefer small funds over larger ones. The authors also show that small funds are among the top performers, and are underrepresented among the bottom ones. Small funds have also been shown to perform better when investing in illiquid, rather than liquid, stocks (Chen et al, 2004).

The positive relationship between size and performance has also been made for mutual funds in the Swedish market (Dahlquist et al, 2000); one explanation given is that equity focused funds simply might be too large for the markets they are trading in, whilst smaller funds might be more nimble in such markets and thus perform better.

The under-performance of large funds is also connected to liquidity costs relating to getting in and out of trades involving large volumes (Ding et al, 2009). Ding et al show that small funds outperform larger ones on an absolute return basis, but not on a risk-adjusted basis. It is important to note however, that the return profiles of hedge funds and CTA:s are very different from that of mutual funds (Fung & Hsieh, 2000).

Dahlquist et al find a negative relationship between high fees funds and performance. The relationship organization and performance has also been investigated in the literature on fund performance (Chen et al, 2004), where it is argued that organizational dis-economies account for the negative size

effect on performance.

### C.3 Predictability of CTA programs

Is it really possible to predict, whether a certain managed futures program will be a good investment or not? Should one be able to predict returns at all? These are important questions worth pondering about, though this paper will not focus on the predictability aspect.

Papers written about managed futures program strategies are scarce, and the little written about the subject focuses on forecasting, i.e. predictability. Trying to predict managed futures program returns based on historical data using correlation methods has been tested without success (Irwin et al, 1994). Looking at hedge fund returns in general, multi-factor models have been tested; unsuccessfully, here as well (Carhart, 1997). The unsuccessful results shown by the papers mentioned is to be expected however, as the papers are based on linear models, trying to explain non-linear relationships. Hedge fund returns, and managed futures program returns in particular, have been shown to exhibit fat tails and skewness, i.e. non-normal distributions

The predictability of CTA program returns have been inconclusive, based on which methods have been used (Irwin et al, 1994; Abdou & Nasereddin 2011). Tests using hedge fund strategies also showed no predictive power (Abdou & Nasereddin, 2011). For hedge funds in general however, certain authors have found evidence of the predictability of returns (Avramov et al, 2009).

Irwin (1994) uses correlations to try and check for predictability of returns, whilst Abdou and Nasereddin (2011) use a Support Vector Machine (SVM) regression approach when looking at hedge fund return data. The difference lies in the assumptions made about the data analyzed; i.e. correlations assumes that the relationship between CTA program returns and the independent variables is linear, whilst SVM does not (i.e. the method supports non-linear relationships, and makes no assumptions regarding the distribution of the programs). The paper of Abdou and Nasereddin (2011) mainly compares the performance of Artificial Neural Networks (ANN, also a learning algorithm method) with those of the SVM, finding that the SVM yields better results. Yet, the paper has not tested the tool in real life. Nor do they analyze the actual results generated by the SVM model.

How about other performance variables, other than returns?

Newedge (Newedge, Oct 15 2009) states that correlations and volatility of portfolio CTA:s can be predictable, and that one should look for low correlations when building portfolios comprising of CTA:s. They also found that past returns were not predictable (surprise). Regarding volatility, Irwin (1994) also found this variable to be predictable for CTA programs.

Predictability has always been at the focus of mutual fund and hedge fund academic as well as practitioner attention. Yet, one need to pose the valid and potent question: why do we expect to see patterns, to predict markets we know generate extreme outlier values, values that we expect to happen in order to make a profit? Being outliers, their very nature makes them unpredictable.

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