Imperial College London
Imperial College Business School

The Performance Persistence, Flow and Survival of Systematic and Discretionary Commodity Trading Advisors (CTAs)

Julia Arnold

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Declaration

I hereby declare that this thesis submitted for the degree of Doctor of Philosophy is my own work and that the data here presented, unless otherwise stated, has been collected by me.

Abstract

This thesis studies the performance, performance persistence, survival and flow of Commodity Trading Advisors, also known as CTAs or Managed Futures Funds. One of the main contributions of this thesis is the novel classification of CTA strategies. This is obtained by hand-collecting information frequently by directly contacting the funds in the database. I thus identify two main trading styles: Systematic and Discretionary CTAs which are the main focus of this thesis. I further separate Systematic CTAs into trend-followers with differing trading horizon. This novel dataset allows me to reconsider many hitherto studied issues in the CTA space with an application to these sub-strategies.

The first section investigates the differences in mortality between Systematic and Discretionary CTAs, over the longest horizon than of any in the literature. A detailed survival analysis over the full range of CTA strategies is provided. Systematic CTAs have a higher median survival than Discretionary CTAs, 12 vs. 8 years. I hand collect information on reasons for exit from the database. I propose new filters that will better identify real failures among funds in the graveyard database. Separating graveyard funds into real failure I re-examine the attrition rate of CTAs. The real failure rate is 11.1%, lower than the average yearly attrition rate of 17.3% of CTAs. The effect of various covariates including several downside risk measures is investigated in predicting CTA failure. Controlling for performance, HWM, minimum investment, fund age and lockup, funds with higher downside risk measures have a higher hazard rate. Compared to other downside risk measures, the volatility of returns is less able to predict failure. Funds that receive larger inflows are able to survive longer than funds that do not. Large

Systematic CTAs have the highest probability of survival.

The second part studies the performance and performance persistence of Systematic and Discretionary CTAs. Controlling for biases, after fees the average CTA is able to add value. These results are strongest for large Systematic CTAs. I extend the seven-factor model of Fung-Hsieh (2004a) and find that this model is better able to explain the returns of Systematic rather than Discretionary CTAs. I find three structural breaks in the risk loadings of CTAs different to hedge fund breaks: September 1998, March 2003 and July 2007. Using these breaks I show that systematic CTAs were able to deliver significant alpha in every sub-period. I also find evidence of significant performance persistence. However, these findings are heavily contingent on the strategy followed: the persistence of Discretionary CTAs is driven by small funds whereas large funds drive the performance persistence of Systematic funds. These results have important implications for institutional investors who face capital allocation constraints. They also suggest that contrary to the previous findings, the CTA industry does not appear to be heading towards zero alpha.

The final section looks at the relationship between fund-flows and performance. Investors chase past performance, the fund- flow -performance is significant and concave for some strategies. Although there is some long-term performance persistence of Systematic funds with the highest inflows, there is no smart money effect in the CTA literature. I find no evidence of capacity constraints among Systematic CTAs. Investors are thus not able to smartly allocate funds to future best performers and take full advantage of the liquidity that CTAs offer.

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Dedication

To my husband James Arnold, my son Maximilian Arnold, my parents and to my late grandmother Nadia.

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Introduction

This thesis focuses on CTAs, also known as Commodity Trading Advisors or Managed Futures Funds, a subgroup of hedge funds which accounts for approximately 10% of all hedge funds[1], with a total AUM as of December 2012 of US$329.6B[2]. The term CTA represents an industry of money managers who accept compensation for trading on behalf of their clients in the global futures and forwards markets. Originally these funds operated predominantly in the commodities markets but today they trade in liquid futures, forwards and other financial derivatives. Gorton and Rouwenhorst (2004) find that the risk premium on commodity futures is the same as equities, but commodity futures are negatively correlated with equity and bond returns. Assets held in CTAs have been growing steadily, notwithstanding the recent financial crisis of 2008, and their double digit performance has attracted deserved attention. CTAs have also received attention from academics, who have documented several interesting facts: Firstly, CTAs differ from hedge funds in terms of trading strategies (see for example Fung and Hsieh (1997b) who show that CTAs follow trend-following strategies). Secondly CTAs differ from hedge funds in terms of attrition rates and survivorship bias, Liang (2004) and liquidities, Getmansky, Lo and Makarov (2004). Some studies have suggested that

[1] Joenvaara et al. (2012)
[2] Assets reported from BarclayHedge CTA database.

CTAs have nonlinear correlations with traditional assets, stocks and bonds, and have positive skewness (Vuille and Crisan (2004)). Thus CTAs also differ from hedge funds in terms of correlation structures in different market environments and are therefore a good diversification tool for portfolios of stocks, bonds and hedge funds (see earlier work by Lintner (1983), Edwards and Park (1996) and Billingsley and Chance (1996)). Kat (2002) and Edwards and Caglayan (2001) documented that adding CTAs to a portfolio would allow investors to achieve a substantial reduction in volatility whilst providing protection during bear markets. This could be attributed to the strategies employed by CTAs. Most CTAs describe themselves as trend-followers. Fung and Hsieh (1997b) show that the returns of the trend-following funds can be replicated using portfolios of lookback straddles. Kazemi and Li (2010) further document that CTAs have market-timing ability rather security selection and systematic CTAs are more skilled at market timing than their discretionary counter parts.

Given the growing interest in this asset class, this thesis builds on earlier CTA literature, by analysing the performance, performance persistence, survival and asset flow of CTAs. However, unlike earlier literature that mainly treats CTAs as one group of funds, this thesis identifies and analyses the differences between the two main CTA trading styles: systematic and discretionary. A recent Financial Times article[3] highlights the differences between systematic and discretionary CTAs: *"Should investors favour the systematic approach, sometimes known as the black box approach, that relies on computers responding to the asset selection instructions programmed into it and removes any element of panic in attempting to ride changes in market conditions? Or should they favour the discretionary approach that relies on the instinct and experience*

[3]The Financial Times, June 9, 2012, "A true CTA will stick to chosen path." by Brian Bollen.

of humans who can smell a significant change in markets and take the necessary steps to avoid unwanted volatility?" The systematic approach relies heavily on quantitative models that generate buy and sell signals. These funds are fully automated and are fine tuned over time to adapt to changing market environments. Discretionary funds, on the other hand, base their strategies on fundamental or technical indicators or both and rely heavily on a single manager. Thus the experience of the manager becomes key. Most of the systems used by both types of funds are either trend-following, counter-trend or some may engage in spread/relative value strategies. Trend-followers do not predict trends but rather jump on them once they are identified by the system, following moving averages or momentum indicators.

Given the differences in trading approach between systematic and discretionary funds, there is much debate among practitioners between the advantages of the two systems. The above mentioned article from the Financial Times addresses some points: *"Systematic trading takes the emotional element out of trading. Systematic allows for historical back and forward testing of the trading model. Systematic allows the CTA to trade in multiple markets simultaneously. It also removes some of the key personnel risk. If a trader or portfolio manager leaves the firm, the CTA can still use the same model. Advantages of the discretionary approach include the ability to move quickly to put on or take off positions."* However, the article notes that discretionary trading has some limitations: *"It can be difficult to remove emotional elements from trading. It can be difficult for one person to trade multiple markets simultaneously. If the decision-making person leaves the firm, it could be tricky to maintain the same trading methods or ideas."* Thus the arguments point to some advantages of systematic trading over discretionary. Does the evidence support this view? In this thesis I aim to answer this question by addressing the differences in survival, performance and performance persistence and the effect of flows on performance between systematic and discretionary CTAs.

The first part of this thesis addresses the differences in mortality between systematic and discretionary CTAs. If discretionary CTAs are more affected by the behavioral elements of human trading as well as key man risk then this will likely have an impact on the survival of discretionary funds. Risk management is key to the success and survival of a CTA over the long-term. CTAs will try and jump on every possible trend, with the success of the strategy dependent on a successful stop-loss policy. Algorithmic trading may provide a more reliable exit to unprofitable trades, rather than human judgement impaired by emotions which could lower fund survival rates. With this hypothesis I look at at the survival rates of the two trading systems.

Literature on CTA survival is rather sparse. This study makes several contributions to the literature on CTA failure. Firstly, unlike previous research on CTA survival (Brown, Goetzmann and Park (2001), Rouah (2005) and Gregoriou, Hubner, Papageorgiou and Rouah (2005)) this study distinguishes the "real failure rate" from the attrition rate of CTAs. This is not the first study to distinguish failure rate from attrition rate. Previous studies have addressed this issue in the hedge fund literature only, Liang and Park (2010). Defining failure in the hedge fund and CTA literature is a significant challenge as information on the reasons for exit from the database is rarely available. To circumvent this problem I hand collected information on liquidation by directly contacting many of the funds in the database, searching extensively on the internet and collecting information from private sources. I am able to show that the filters proposed in the previous hedge fund studies to distinguish failure rate are incomplete or at least are not entirely appropriate for CTA data and provide extensions that allow one to discriminate between truly failed funds and those that liquidated for other reasons or are in the graveyard because they simply stopped reporting to a database. Using this information I re-examine attrition in the CTA industry. I find that the real failure rate is in fact 11.1% lower than the average attrition rate of 17.3% and much lower than previously documented levels. I also show that the failure rate of systematic CTAs is lower than that of discretionary funds, 10.4% vs. 12.2% with an even larger difference in the attrition rates. I further study fund survival and find that the median survival of systematic CTAs is significantly higher than the previously reported median survival for the entire CTA industry, 12 years vs. 2 years reported in Brown, Goetzmann and Park (2001).

To pursue the survival issue further, I investigate the factors that determine manager exit from the industry. Unlike previous studies on CTA survival, I use Cox (1972) proportional hazards (PH) model with time-varying coefficients rather than fixed coefficients and incorporate various downside risk measures. I implement a survival analysis for each of the three definitions: i) attrition, ii) liquidation and iii) failure. Explicitly separating real failure from discretionary closures in the survival model avoids blurring the effect of predictor variables on survival, Rouah (2005). The results of this analysis show that CTA survival is heavily contingent on the strategy followed by the fund. Secondly, size and fund-flows have a positive effect on CTA survival. Furthermore, with the addition of other downside risk measures, standard deviation loses its explanatory power. Finally, systematic and in particular large systematic CTAs have the lowest probability of failure.

In the second part of the thesis, I present new stylized facts about CTA data biases, performance and performance persistence. Before using data on CTAs one must address and minimize data biases. These according to Fung and Hsieh (2009), although well documented in the literature, need to be updated in light of the recent financial crisis. I find that despite an increase in the attrition rate during 2008 and 2009, the effect on survivorship bias is negligible and results remain consistent with earlier literature: Survivorship bias for CTAs for the period 1993 to 2010 remains at 3.92% similar to the 3% reported by Fung and Hsieh (1997b). The effect of instant history bias is also shown to be in line with earlier results in the literature[4]. Using this bias-adjusted data, I provide evidence suggesting that the average CTA is able to deliver positive and economically as well as statistically significant risk-adjusted performance. More specifically, the aggregate equally-weighted index of excess returns of all CTAs earns 0.55% per month in excess of T-Bills. This is higher than documented by Bhardwaj (2008) and contrary to his arguments and the negative publicity of Elton et al. (1991) is suggestive that CTAs on average do add value. Secondly, I show the average performance is sensitive to the CTA strategy employed. In particular, the excess return of a value-weighted portfolio of systematic CTAs delivers an annualized return of 7.08% whilst for discretionary CTAs it is 4.68%. The highest Sharpe ratio is achieved by systematic short-term trend-followers. This points to the fact that unlike hedge funds, the performance of systematic CTAs is driven by large funds rather than small funds. The annualized excess return of an equally-weighted portfolio of discretionary funds is higher than the annualised excess return of an equally-weighted portfolio of systematic funds, indicating that the performance of discretionary funds is driven by small funds. The performance of discretionary CTAs has thus similar characteristics to that of hedge funds, Joenvaara et al. (2012), Teo (2010).

[4] Fung and Hsieh (2000), Bhardwaj (2008).

I further evaluate the risk attributions of CTAs and examine whether the average CTA is able to deliver alpha. To that end, I recognise that the risk exposures are likely to change over time, see Bollen and Whaley (2009) and Patton and Ramadorai (2011), hence a static analysis will not be appropriate. Fung, Hsieh, Naik and Ramadorai (2008) identify structural breaks in the hedge fund risk exposures. I extend their results to the CTA data and show that the structural breaks for systematic CTAs are not the same as for hedge funds and discretionary CTAs. In particular I show that these breaks appear to be influenced by the changes in interest rates regimes as well as stock market events. Using these breaks, I apply the seven factor Fung-Hsieh (2004) model, extended with additional trend-following factors and the GSCI index and show that this model together with structural breaks is better suited to systematic CTAs rather than discretionary funds: The adjusted R^2 for systematic CTAs is 51.2% and 29.3% for discretionary CTAs. This indicates that systematic funds use trend-following strategies more consistently than discretionary funds. This resonates with the results of Kazemi and Li (2009) and points to momentum strategies being pursued by systematic CTAs. I also show that trend-following systematic CTAs were able to deliver statistically significant alpha in every sub-period and that contrary to the results of Fung et al. (2008) for hedge funds, alpha does not appear to be heading towards zero. This poses a challenge to the Berk and Green (2004) rational model of active portfolio management. To that end, I also investigate the issue of performance persistence. Previous studies on hedge funds found evidence of short-term performance persistence, Agarwal and Naik (2000a) and (2000b) and Baquero et al. (2005). Others using more robust econometric techniques found evidence of long-term persistence, Kosowski et al. (2007), Jaganathan, Novikov and Malakov (2010) and Boyson (2008). Sorting on the t-statistics of alpha, I find evidence of short-term performance persistence for discretionary funds and only long-term performance persistence for systematic funds. Furthermore, these results appear to be sensitive to rebalancing frequency, fund strategy and fund size. In particular, contrary to the results in the hedge fund literature, Teo (2010), the performance persistence of systematic CTAs is driven by large funds. These results lead to another question: In light of the recent increase in assets flows to the CTA industry, is there evidence of a fund flow-performance relationship and are there any capacity constraints.

In the last part of this thesis, I analyse the fund flow-performance relationship of systematic and discretionary CTAs. To the best of my knowledge, the flow-performance relationship as well as the hypothesis of capacity constraints among CTA strategies has not been examined rigorously in the academic literature. The only analysis which concentrates on CTAs exclusively is by Do, Faff, Lajbcygier and Veeraraghavan (2010), however their study treats CTAs as one group. To study the fund flow-performance relationship I use yearly (used in most hedge fund studies[5]) as well as quarterly data. I employ piecewise linear regression to model the non-linearity of the relationship. I find that contrary to the conclusions of Ding, Getmansky, Liang and Wermers (2009), the shape of the relationship is not driven by the presence of share restrictions. Instead, time horizon, fund size and strategy have an effect on the fund flow-performance relationship. In particular, using quarterly rather than annual data I find a linear relationship for all CTAs, but concave relationship for small discretionary CTAs. I find that the relationship of systematic CTAs remains linear and is driven by large funds.

I further analyse the effect of fund inflows on performance persistence. For discretionary CTAs, I find no evidence of long-term performance persistence, but there is

[5]See Ding, Getmansky, Liang and Wermers (2009).

some evidence on a quarterly horizon when inflows are taken into account. I document evidence of long-term performance persistence for systematic CTAs even in the presence of inflows. Furthermore, consistent with earlier findings this is driven by large funds. This points to a lack of capacity constraints among these funds. To that end, I rigorously test for the presence of capacity constraints in the CTA sub-strategies using two methodologies. I find no evidence of capacity constraints among systematic CTAs despite the large inflows into these funds. I show that over the period 1993 to December 2010, systematic CTAs received more asset inflows than discretionary funds. This shows that investors are able to discriminate between the two types of funds and are thus aware of the advantages and disadvantages of the two strategies. I therefore test for the smart-money effect in the CTA industry. Smart-money being defined as the ability of investors to infer the skill of a fund manager and consequently allocate more money to those managers, subsequently receiving superior returns in the next period than the remaining universe of investors. Applying various methodologies and consistent with the earlier results in the literature, I am unable to find any smart-money effect either for systematic or discretionary CTAs: Investors do not appear to be able to fully exploit the liquidity that CTAs provide.

Chapter 1

Survival of Commodity Trading Advisors

1.1 Introduction

Over the last decade, the CTA and hedge fund industry has more than doubled in both size and number of funds. Estimates indicate that, at its peak in the summer of 2008, the entire industry managed around US$2.5 trillion. The impact of the financial crisis of 2008-2009, however, has clearly been felt by the hedge fund and CTA industries. The crisis is arguably the largest in modern financial history and has led assets under management to fall sharply via a combination of trading losses and investor withdrawals. Although assets under management have decreased in the hedge fund industry as a whole, they have increased slightly in the CTA industry over the course of this crisis. BarclayHedge reports a level of assets under management for CTAs of over US$200 billion for the end of 2009. In addition, around 50% of funds have less than US$10 million in assets, suggesting a high number of new entrants into the industry. The rapid growth of the CTA and hedge fund industries has also been accompanied by a growth in the number and severity of failures, however. Investors recognize that whilst hedge funds and CTAs may produce high expected returns they may also expose investors to potentially large downside risks.

The term CTA represents an industry of money managers known as Commodity Trading Advisors who accept compensation for trading on behalf of their clients in the global futures and forwards markets. These funds originally operated predominantly in commodities markets but today they invest in liquid futures and forwards markets in commodities, currencies, fixed income and equity indices. CTAs are usually self-regulated and registered with the National Futures Association (NFA), a self-regulatory organization for futures and options markets. CTAs are known to have unique risks and nonlinear returns. Fung and Hsieh (1997b) documented CTAs to have nonlinear and non-normal payoffs due to their dynamic trading strategies and use of derivatives. Some of the previous research suggests that CTAs demonstrate positive skewness and excess kurtosis and a rejection of the Jarque-Bera (1980) test for normality.[1] Like hedge funds, CTAs charge a management fee and, in particular, an incentive fee which some have argued may create an incentive for excessive risk taking.

An important issue for both private and institutional investors is how to best achieve a targeted return with an acceptable level of risk. A possible solution would be a diversified portfolio with a certain portion allocated to managed futures. Lintner (1983) showed that the risk-adjusted return of a portfolio of stocks and bonds exhibits substantially less variance at every level of expected return when combined with managed futures. Yet a much debated issue remains whether managed futures have done well

[1] See Liang (2004), Park (1995), Edwards and Park (1996), Gregoriou and Rouah (2004), Schneeweis and Georgiev (2002).

enough on a stand alone basis to justify the high fees that they charge, Amin and Kat (2004), Kosowski, Naik and Teo (2007), Liang (1999), Liang (2001) and Bhardwaj, Gorton and Rouwenhorst (2008). In order to properly address the performance issue one needs to first account for the mortality and survivorship bias associated with these funds. Moreover, while historically most of the money held by CTAs and hedge funds was from high-net-worth individuals, recent growth in assets under management has been from institutional investors such as pension plans and insurance companies. Unlike private high-net-worth individuals, to meet their obligations institutional investors need to allocate capital on a long-term basis with reliable return streams. Selecting alternative investments that are likely to produce stable returns and remain in operation is, therefore, of particular interest to these investors. Survival analysis can be useful as it can provide additional due diligence and aid the selection of funds that are less likely to liquidate.

The study of survival in the CTA industry is sparse and in its virtual infancy. Although previous literature points to a higher attrition rate for CTAs relative to hedge funds, Brown, Goetzmann and Park (2001), these studies do not take into account extreme market events, simply due to their limited data sample. A few studies, however, have shown that CTAs provide downside protection during bear market conditions.[2] Analyzing survival during the recent financial crisis is of particular interest to investors who have become ever more cautious investing in hedge funds. This thesis provides a detailed survival analysis over a new range of CTA classifications and encompasses the longest time horizon of any examined in the literature, including the recent financial

[2] Edwards and Caglayan (2001), Fung and Hsieh (1997b) and Liang (2004).

crisis of 2008.[3] In doing so, it makes several contributions. The first is to distinguish the real failure rate from the attrition rate of CTAs. By clarifying the definition of real failure, despite the fact that to date all CTA studies have deemed the two concepts as one, it is possible to estimate a real failure rate of the CTA industry over the longest period so far studied. Secondly, it finds that CTA survival is heavily dependent on the strategy of CTAs. Whilst Baquero et al. (2005) and Liang and Park (2010) find that hedge fund style is a factor in explaining hedge fund survival, Gregoriou et al. (2005) examine survival over a range of CTA classifications and find that survival is heavily related to the strategy of the CTA. Whilst these authors use the CTA classifications directly provided by the BarclayHedge database, this study makes an important contribution by reclassifying CTAs into two main trading styles: systematic and discretionary, and shows how survival is related to these styles. The life expectancy of CTAs is investigated at the aggregate level and for all classifications, whilst the impact of various variables on survival is analyzed.

Hedge fund databases provide information on live and dead funds. Funds no longer reporting to the database are moved into the "Graveyard". Fung and Hsieh (2002), however, point out that not all funds listed in the graveyard database have in fact liquidated. Many stopped reporting for a variety of other reasons, including merging with another fund, name change, etc. Earlier studies on hedge funds and CTAs have regarded moving to the graveyard as representing liquidation and failure and the attrition rates estimated by previous research have all been based on this classification. Defining failure is particularly challenging as it is difficult to obtain information on the

[3] Fung and Hsieh (2009) note that as capital flows out of the hedge fund and CTA industry at an unprecedented rate, the attrition rate is likely to rise. The full impact of the contraction of the assets may take some time to manifest itself however. "Consequently the liquidation statistics from the second half of 2009 are likely to be important in estimating survivorship bias."

reasons for exit in respect to the defunct funds, although a few databases do provide such information. In this regard, an important contribution offered by Rouah (2005) was explicitly to examine fundamental differences between different types of exits in hedge fund data. His study was implemented using the HFR database which provides three drop reason categories: liquidated, stopped reporting and closed to new investment. As such, Rouah (2005) study was able to examine the effect of different exit types on attrition statistics, survivorship bias and the survival analysis of hedge funds. When liquidation only was considered the average annualized attrition rate dropped to 3-5% and the bias associated with using only live funds and funds that stopped reporting, the survivorship bias, increased to 4.6%.[4] A recent study by Liang and Park (2010) on hedge funds also accounts for the potential shortcomings of using the entire Graveyard database, or even just liquidated funds, as failures. Even though some databases provide information on liquidated funds, the authors argue that even liquidation does not necessarily mean failure, as some funds may liquidate for other reasons. The authors, therefore, propose a filtering system based on fund past performance and past asset flow analysis to distinguish failed funds from those that had voluntary closures. Using this new dataset, the authors reexamine the effects that contribute to real failure. To date, there are no comparative studies for CTAs exclusively, however. Furthermore, Liang and Park (2010) explicitly exclude managed futures from their hedge fund sample.

Early studies on CTAs regarded the entire graveyard as an indication of failure because on average such funds had poor performance, Gregoriou (2002). The attrition

[4] The biases present in the hedge fund and CTA data and its effects on performance are well documented in the literature (Ackermann, McEnally and Ravenscraft (1999), Fung and Hsieh (2000b), Diz (1999a), Brown, Goetzmann, Ibbotson and Ross (1992), Fung and Hsieh (1997b) and Carpenter and Lynch (1999)), however none of the previous studies have accounted for the different exit types. As such, Rouah (2005) is the first to demonstrate the effect of different exit types on survivorship bias.

rate results estimated by previous studies are all based on such a classification. Thus previous literature on CTAs suggest that they experience lower survival than hedge funds (see Brown, Goetzmann and Park (2001), Liang (2004)). Brown et al. (2001) determine that the attrition of CTAs is 20% versus 15% for hedge funds. Liang (2004) uses HFR data for the period 1994-2003 and estimates that hedge funds have an attrition of 13.23% in bull markets and 16.7% in bear markets, whilst CTAs have an average attrition of 23.5%. Getmansky, Lo and Mei (2004) also find that managed futures have the highest average annualized attrition rate, compared to other hedge fund strategies, with a rate of 14.4%. Fung and Hsieh (1997b) and Capocci (2005) also find an attrition of 19%. Spurgin (1999) notes that the mortality of CTAs reached 22% in 1994. Two recent studies however find conflicting rates. Bhardwaj et al. (2008) found an attrition rate of 27.8% whilst Xu, Liu and Loviscek (2010) found a substantially lower rate of 11.96%. Both studies covered the latest period but used different databases. This could account for the difference in results. As stressed by Xu et al. (2010), however, it is important to account for attrition rates in light of the effect of the recent crisis on the industry.

This study extends the most recent advances in survival analysis in the hedge fund literature to CTAs, whilst encompassing the longest time period so far studied for CTAs. To date there appears to have been no study that has analyzed CTA attrition and survival using different exit types. The most recent CTA survival study by Gregoriou, Hubner, Papageorgiou and Rouah (2005) treats all funds in the graveyard as liquidated possibly due to the limitations of their database. In fact the authors explicitly make a strong assumption that all funds in the database that have stopped reporting did so due to poor returns. The authors use the BarclayHedge database for the period 1990-2003.

Unfortunately, BarclayHedge does not provide exit reasons for many funds in the graveyard. While, this study also employs BarclayHedge, since it provides the most extensive database of CTAs, it builds on the methodology of Liang and Park (2010) to identify failures in the CTA graveyard. One of the key contributions of this study is to extend the failure filters proposed by Liang and Park (2010); it shows that their two return and AUM filters are incomplete and applies extended filters to the BarclayHedge database to reclassify the exit types of the graveyard into those that liquidated and those that are alive but no longer report. It also separates real failures from liquidated funds. These new criteria are based on an examination of all available information on defunct funds. Many of the funds in the database have been contacted to confirm their liquidation status and reason for exit. Certain information was obtained from private commercial sources and extensive internet searches.

The second contribution of this study is to reclassify the entire CTA database into investment styles that are more commonly used in the industry. Unlike previous research, therefore, CTAs are separated into two distinct styles: Systematic and Discretionary. Systematic CTAs base their trading on technical models devised through rigorous statistical and historical analysis. Investment decisions are made algorithmically and thus all the rules are applied consistently and there is limited uncertainty as to their application. The last decade has witnessed an increase in the complexity and breadth of quantitative financial research; an increase that has been fueled by the greater availability of financial and economic data as a result of the relentless increase in computing power. Systematic trading that requires intensive quantitative research and the use of sophisticated computer models has thus become more prevalent. Most of the entrants into this field are trained scientists and engineers. Park, Tanrikulu and Wang (2009) argue that systematic traders may hold significant advantages over discretionary traders. Even though discretionary traders may also follow trends they still base their trading decisions on manager discretion. Thus one of the challenges facing discretionary traders is the control of human emotion in reacting to difficult market conditions. Systematic programs do not have this weakness as all the trades are executed by the program. In addition there is a lesser “key man risk” which tends to be associated with discretionary traders. Due to their automated nature, systematic funds have the further advantage of scalability across a multitude of markets and they can thus accept more capital whilst allowing for more diversification across markets, strategies employed and number of trades. In light of these differences, it is of interest to test empirically the survival rates associated with the two strategies. A recent study by Kazemi and Li (2010) also classifies CTAs into these two manager categories and finds that there are differences in the market timing abilities of systematic and discretionary CTAs, notably that systematic CTAs are generally better at market timing than discretionary CTAs. This study however, further breaks systematic funds into sub-strategies. Park, Tanrikulu and Wang (2009) note that systematic CTAs are comprised of multiple strategies most of which can be classified as either trend-following or relative value. Others employ trading models that fall into neither of these categories, e.g. pattern recognition and counter trend. Trend-following strategies are also split into programs that primarily use short-term, medium-term or long-term signals or holding periods. Based on the previous research, one would expect the findings of this study to indicate that systematic CTAs have better performance and higher survival than discretionary funds, since the lack of the human emotion element allows for better risk control and a consequent reduction in the risk of failure.

Using the classification of investment styles and the failure filtering system discussed above, the average annual attrition rate of the entire CTA database is found to be 17.3% for the 1994-2009 period, i.e. similar to previous studies. The failure rate, however, is significantly lower at 11.1%. There are also differences between systematic and discretionary funds, with systematic funds having lower attrition and failure rates of 16.0% and 10.4% versus 21.6% and 12.6% respectively. The BarclayHedge database contains a significant number of funds with less than US$10 million under management. After removing such funds, the average attrition and failure rates drop to 7.8% and 4.1% for systematic and 10.8% and 5.9% for discretionary funds. These are lower than previously estimated but comparable to the findings of Rouah (2005) and Liang and Park (2010) for hedge funds. The results suggest that the attrition rate of CTAs may not be as high as previously suggested and in particular systematic CTAs have a lower attrition rate than discretionary CTAs.

Survival analysis is then implemented to determine factors affecting CTA failure. There are a few studies in the hedge fund literature analyzing the effect of various variables on survival, including: Liang (2000), Brown, Goetzmann and Park (2001), Gregoriou (2002), Baquero, Horst and Verbeek (2005), Rouah (2005), Ng (2008) and Baba and Goko (2009). In particular Brown, Goetzmann and Park (2001) find that hedge fund survival depends on absolute as well as relative performance, seasoning and volatility. Recently, Brown, Goetzmann, Liang and Schwarz (2009) estimated the effect of operational risk on hedge fund survival. Using novel data from SEC filings (Form ADV) in combination with the TASS database, the study developed a quantitative model, the ω-score, to quantify operational risk and use it as a predictor in the Cox (1972) proportional hazards model to predict its effect on hedge fund survival. The study included managed futures as a sub-strategy but found that the coefficient of operational risk was insignificant for managed futures and the direction of its effect was blurred. The score was related to conflict-of-interest issues, concentrated ownership and reduced leverage, none of which seem to explain CTA survival. Other studies on CTA survival are rather sparse, Diz (1999a), (1999b), Spurgin (1999) and Gregoriou et al. (2005) each analysed CTA survival separately from hedge funds. The most recent of these analyses is that of Gregoriou et al. (2005) who find that performance, size and management fees have an effect on CTA survival. The influence of volatility appears rather limited.

The particular contribution of this study is to employ downside risk measures that incorporate higher return moments in predicting CTA failure. In doing so it incorporates time varying as well as fixed covariates. The methodology closely follows that of Liang and Park (2010), who show that these measures are better able to capture the non-normality of hedge fund returns. Incorporating additional risk measures is of particular interest in respect to CTAs who have positive skewness yet can experience large losses. Drawdown as a risk measure is also considered since this can be useful in predicting failure. Lang, Gupta and Prestbo (2006), in fact, argue that drawdowns are the single most significant factor that determines the likelihood of hedge fund survival. Another contribution of this study is to employ Cox (1972) proportional hazard's model with time-varying covariates. This is an improvement to the Gregoriou et al. (2005) model for CTAs who employ Cox's (1972) proportional hazard model with fixed covariates only. By using time dependent covariates new risk measures as well as other covariates are allowed to change with time. Finally, the aim of the study is to build a forecasting model with better warning signals for possible fund liquidations. In order to do this as accurately as possible, the survival analysis for three different definitions of failure is compared: i) attrition, ii) liquidation and iii) real failure. The results show that standard deviation is not an appropriate risk measure in predicting the type of failure and that downside risk measures are better able to explain real failure. As a result, this study finds that systematic CTAs should be favoured by investors due to their significantly higher survival than their discretionary counterparts.

The rest of chapter one of the thesis is organized as follows. Section 1.2 describes the data. Section 1.3 explains the methods. Section 1.4 provides the empirical results and robustness tests and section 1.5 concludes.

1.2 Data

There are several databases that collect data on CTAs. The most commonly used databases in academic studies are TASS, CISDM and BarclayHedge. To analyze the attrition and survival of CTAs properly this study uses monthly net-of-fees returns from live and dead CTAs that reported to the BarclayHedge database, proprietor of one of the most comprehensive commercially available databases of CTAs and CTA performance. The sample period under examination in this study is from January 1994 to December 2009, a total of 192 months: a time period that spans both bull (pre 2000 and 2003-2007) and bear markets, such as the bursting of the tech bubble in the spring of 2000 and, importantly, the financial crisis of 2007-2009. This constitutes the longest period used to date to examine CTA survival. BarclayHedge provides a variety of information other than performance. It collects fund names, management company, AUM, minimum investment, start and ending dates, investment style, management and incentive fees, HWM, leverage, fund status, share restrictions, and others. It is important to note that all the information contained in these databases is reported on a strictly voluntary basis only.

The BarclayHedge database consists of both active "Live" and "Defunct" funds. The database is divided into two separate parts: "Live" and "Graveyard" funds. Funds that are in the live database are ones that are still operating and continue to provide updates on their performance. Once a fund stops reporting for three consecutive months, the fund is moved into the Graveyard. A fund can only be in a Graveyard once it has been listed in the live database. As of the end of December 2009, there were 3436 funds in the combined database. Out of these, 1,016 were live funds and 2,420 were defunct funds. The majority of the funds report their returns net of management and incentive fees. I eliminate from my sample funds that report quarterly or gross returns, a total of 15 funds. I also remove various long only funds and index trackers, duplicate entries due to multiple share classes, onshore and offshore vehicles, leveraged versions and various feeder structures and funds born prior to 1994.[5] This leaves 696 live funds and 1750 defunct funds. I also remove all multi-manager funds. In words of Liang (2005), "Combining CTAs with funds that manage several CTAs would not only cause double counting problem but would also hide the differences in fee structures between CTAs and fund-of-funds." To eliminate backfill bias, for the empirical analysis I impose an additional filter in which I require funds to have at least 24 months of non-missing returns.

[5]Figure 1.1 was constructed using all the share classes and onshore and offshore vehicles so as to capture total assets under management accurately across the industry.

1.2.1 Style Classification

Hedge funds are not allowed to solicit the general public, therefore detailed strategy information is not included in the databases. In addition, several data vendors like TASS do not include fund identities in their academic versions making it impossible to collect information on funds from other sources. In this study, however, I had access to fund identities that allowed me to access information through fund websites, other sources such as Alphametrix, as well as private sources, to get a fuller understanding of each fund's strategy. Narang (2009) and Rami (2009) also provided a basis to understand the complexities of the different CTA strategies. This has allowed me to segregate CTA funds into various strategies. I therefore used funds' self-reported strategy description in addition to BarclayHedge categories and hand collected information and am therefore the first to classify CTAs in this manner.

BarclayHedge classifies funds into several investment styles. There is currently no universally accepted form with which to classify CTAs into different strategy classes. There is some form of consensus emerging in the literature as to how best to classify various hedge fund strategies, however nothing similar yet exists for CTAs. In fact, most of the earlier literature treated CTAs as a single group. Recently, some studies classified CTAs into different investment styles but these have all done so in a different manner. Gregoriou et al. (2005) grouped the BarclayHedge classifications into five categories, yet in their 2010 paper the same authors arrived at twelve classifications from the same database. Capocci (2005), meanwhile, grouped the same dataset into ten classifications. All of these authors have used the BarclayHedge database yet have created different strategy classes. It is also unclear how previous studies arrived at their classifications since most funds in BarclayHedge would frequently fall into several categories representing trading style and asset class utilized. For example, a fund may select itself to be both systematic and technical diversified, yet the authors would have both of these as a separate category. In this study therefore, I propose a different CTA style classification based on the one used in the industry.

Firstly, I note that almost all funds fall into one of the three main categories based on their self-reported trading strategies: i.e. systematic, discretionary and options strategies. Systematic traders systematically apply an alpha-seeking investment strategy that is specified based on exhaustive research. This research is the first step in the creation of a systematic trading strategy. As a result, most new entrants into the industry are trained scientists and engineers. Market phenomena are uncovered with statistical analysis of historical data. Trading algorithms are then constructed to exploit the markets and these are applied consistently. Discretionary CTAs, on the other hand, base their models on manager's discretion. There are several advantages of systematic trading over the discretionary style. Firstly, the emotional element of discretionary trading is removed. Discretionary traders may frequently suffer from *disposition effect*, as documented by Shefrin and Statman (1985): they are quick to realize gains and are slow to realize losses. In essence the main difference between the two always lies in *how* an investment strategy is conceived and implemented rather than what the strategy actually is. Systematic trading takes emotion out of investing and imposes a disciplined approach. Additional benefits are reduction of key man risk, scalability and more diversification in terms of the number of markets analyzed and the types of strategies employed. I separate options strategies into a separate group as I believe they follow substantially different trading strategies compared to systematic and discretionary funds. In particular, options funds engage in either selling options or exploiting arbitrage opportunities using options. My final three main category classification therefore has systematic, discretionary and options CTAs. My classification is in line with recent work of Kazemi and Li (2010) who break their CISDM database into systematic and discretionary CTAs. However, I further their work by breaking systematic funds into several categories: trend-following, pattern recognition and relative value. Trend-following funds are further broken into short-term, medium-term and long-term traders. Billingsley and Chance (1996) also separate CTAs into technical and non-technical funds, where technical funds essentially mirror the systematic funds classified in this study. The authors further note that among those technical funds, the majority are indeed trend-followers.[6] About ten percent of the funds in our database have no BarclayHedge classification, yet when reading their detailed strategy description it is apparent that they still fall into one of the three main categories.

The final count and description for the different investment styles are shown in the Appendix. It is clear from the table that the representation of the investment style is not evenly distributed. Systematic CTAs account for 60% of all CTAs. This is a lower number than the one reported by BarclayHedge, which cites that approximately 80% of all CTAs are systematic. I have employed a more stringent approach to qualify the funds as being systematic, however, and this explains the lower figure in my study. My classification results should still be treated with caution. Due to the nature of the industry and the lack of full information, it is impossible to arrive at strategy assessments with absolute certainty since one is relying on the managers' statements. I also note that among systematic funds, trend-following is the most dominant strategy with 87%

[6] Fung and Hsieh (2001) show that a simple trend following strategy can be modeled using look-back straddles that generate a non-linear payoff structure.

of the funds. The vast majority of trend-followers employ a medium-term frame in a variety of markets. I define short-term as anything between high frequency trading to trades within one week. Indeed high frequency trading has become a popular strategy in the last few years. Medium-term trend-followers are defined as those that use two weeks up to one month trading signals and long-term trend-followers as anything above one month. Among discretionary funds, most utilize either technical or a combination of technical and fundamental approaches. In addition, most funds trade in diversified markets. The Appendix provides a detailed description of strategies.

1.2.2 Distinguishing Discontinuation from Death and Failure

Within those funds assigned to the graveyard database, distinguishing between liquidated funds and those that are in fact still in operation is complicated by the lack of detailed information available on defunct hedge funds. Early studies on hedge funds regarded moving funds to the graveyard as a *de facto* indication of failure. Attrition rate calculations and survival analysis done by previous research is based on just such a broad classification. Recently, however, data vendors began to provide information on reasons for exit. Thus, the TASS database has seven distinct exit classifications: fund liquidated, no longer reporting, unable to contact the manager, closed to new investment, merged into another entity, dormant, unknown. HFR, meanwhile, has only three categories. BarclayHedge only began collecting this information very recently. As a result, this information is only available for a small proportion of funds, the rest are classified as unknown.[7] This is in sharp contrast to other databases such as TASS or HFR. For example, Baquero, Horst and Verbeek (2005) used the TASS database and

[7]Out of 2076 funds in the graveyard, only 435 funds have a recorded reason for not reporting.

had only a small number of funds with an unknown disappearance reason. Rouah (2005) used the HFR database and was able to report exit information for most funds. In this study I employ the BarclayHedge database, however, as it has the advantage of having the widest coverage of CTAs available. The limited nature of its information on exit types, however, renders any meaningful survival analysis all but impossible. To circumvent this problem several studies have proposed various methods to filter for liquidated funds in other databases as well. Baquero, Horst and Verbeek (2005) follow Agarwal, Daniel and Naik's (2004) quarterly flow analysis to make an assessment of the death reason in the TASS database. Their analysis, however, concentrates on liquidation only. Liang and Park (2010), (henceforth, LP) further make a distinction between liquidation and real failure and argue that the classification provided by the databases is not sufficient. Not all liquidated funds fail. Some funds may choose to liquidate based on the market expectations of managers, funds merging, or simply the manager retiring. As a consequence, LP reclassify the database using a performance and fund flow filter system. Utilizing only failed funds they are able to examine the effects that contribute to hedge fund failure.

Survival analysis necessitates clear definition of failure. Rouah (2005) argues that including all the graveyard funds in the database can blur the effect of predictor variables in a survival analysis. I filter all the funds following the three criteria used by LP: all funds in the graveyard, funds with negative average rate of return in the last 6 months, funds with a decrease in assets under management (henceforth, AUM) for the last 12 months. This study finds that these filters would miss some of the liquidated and failed funds. In particular it failed for many small funds in our sample and for many funds that had experienced large losses more than 12 months before the end of data.

Case 1. A failed fund with small AUM.

I found that my sample contained a lot of funds with assets under management of less than US$20 million. Figure 1.1 shows the evolution of AUM in the CTA industry.

[Please insert Figure 1.1 here]

In fact, on average 96% of the total AUM of the industry is managed by funds with assets above US$20 million, yet funds with less than US$20 million under management comprise almost 70% of the total number of funds in our database. Kosowski et al. (2007) argue that funds with less than US$20 million AUM should be excluded from the analysis due to concerns that such funds may be too small for institutional investors. Given the large proportion of these funds in the sample, removing them would greatly reduce the available data. In addition, this study is concerned with establishing attrition and failure rate which necessitates inclusion of all the available data. For the survival model, however, it would be sensible to remove all the funds below the US$20 million threshold.

Figure 1.2 shows an example of Fund A, a liquidated fund with small AUM. The AUM of Fund A remained stable during the twelve months prior to dissolution yet, in terms of downside risk measures, the fund has failed: it had negative average return in the last six and twelve months. Liquidation for small funds is likely to happen quickly without noticeable decline in assets, therefore it would be impossible to filter for these funds using AUM criteria.

[Please insert Figure 1.2 here]

Case 2. Assets lost more than 12 months before end of data.

LP's filters assume very recent failures. Some funds. however, may experience large drawdown followed by loss of assets as investor confidence fails. Still, some funds would continue to report to the database with virtually no assets and good returns until they finally exit. Fund B in Figure 2 is an example of a liquidated fund that continued to report after a large drawdown and loss of assets. LP's criteria would be unable to identify this failure as it happened prior to 12 months before dissolution.

[Please insert Figure 1.3 here]

Case 3. Failure with positive average return in the last six months.

Some funds fail and liquidate yet in the last six months may report a positive average return as they reduce volatility in expectation of liquidation. There is an indication that these funds still continue to report to the database before they eventually shut down. Figure 1.4 shows an example of fund C with a negative annualized compound rate of return, with a loss in AUM, yet it has an positive average rate of return in the last six months.

Case 4. Failure due to a large drawdown 24 months before liquidation.

Fund C is an example of a large fund that suffered a 78% drawdown and lost a majority of its assets, yet it had a positive average return in the last six months. Such a fund would not be picked up by LP's criteria yet it is a clear failure and should be included in the survival model.

[Please insert Figure 1.4 here]

Ng(2008) proposes more a extensive range of filters to identify failures among hedge funds, including the change in AUM 24 months prior to dissolution and the average return in the last 12 months. As has already been mentioned, data in this study is more limited than that used in previous survival analyses since BarclayHedge does not provide reasons for exit for most funds. This study, therefore, separates the graveyard into funds that are still alive but stopped reporting and liquidated funds. It then sorts liquidated funds into those that failed and funds with various discretionary closures. This study follows Agarwal, Daniel and Naik's (2004) AUM flow analysis to make an assessment of the liquidation. Fung et al. (2008), meanwhile, group liquidated funds based on the relative AUM at the end of the fund's life, compared to maximum AUM. I used several filters as it is clear from looking at the previous studies that it is unlikely that one filter can capture all the liquidated funds. In particular I filter for liquidated funds using either of the following criteria:

- Funds with decreased AUM in the last 12 months
- Funds with decreased AUM in the last 24 months
- Funds with very low final AUM relative to the maximum AUM over the fund's lifetime - I use a 70% drop as well as a 60% drop for robustness check
- Funds with AUM equal to 0 in the last month

From the above I obtain two groups of funds; liquidated and not liquidated. Funds that are classified as liquidated by the first set of filters are further sorted into failures or discretionary closures. In particular I calculate the following statistics for all funds and apply them to the "liquidated" set:

- CUM, Annualized cumulative rate of return
- Average return in the last 6, 8, 12 and 24 months

- Annualized standard deviation over entire fund history
- Drawdown in the last 12 and 24 months

Funds that had either negative average returns in the last 6, 8, 12 or 24 months, or negative annualized cumulative returns or a drawdown in the last 12 or 24 months that was significantly higher than annualized standard deviation were classified as *Liquidated Failure*. The rest of the funds were classified as *Liquidated Discretionary Closures*. These are the funds that liquidated for other reasons than bad performance as described in Liang and Park (2010). To test my filtering I contacted many of the funds either by phone or email. The majority of the funds that liquidated but did not experience bad returns were funds that were merging into another fund in the same management company, funds that were going through restructuring or simply a name change, or even retirement of the principal. Hence, these funds would affect the calculation of the liquidation rate but they would not enter into the failure rate. I also checked funds that did not pass the liquidation filters. In many cases these were the funds that had too small an asset base to show a drop in assets but upon contacting them and looking at their returns it was still apparent that they liquidated. There were also some funds that showed no decline in assets nor passed any of the return filter criteria - these were funds that were still active but stopped reporting to the database. Compared to the hedge fund industry the proportion of such funds is not as large, possibly because CTAs would not suffer from the same capacity issues as many hedge funds do: a topic that is thoroughly discussed in the third chapter.

1.2.3 Covariates & Basic Data Description

The covariates used in the survival model include average millions managed, performance, fund age, size, lock-up provision, size volatility, and risk measures as proposed by Liang and Park (2010). This study also adds drawdown to the risk measures. Table 1.1 presents the statistical summary of the data for 2446 funds. The average monthly rate of return is 1.01% with a standard deviation of 6.09%. At the same time the average skewness is positive at 0.33 and average kurtosis is 2.61. This is in contrast to the reported statistics for hedge funds found in Liang and Park (2010) where the mean hedge fund return was 0.62%, negative skewness (-0.04) and kurtosis 5.57. Consistent with previous literature, Table 1.1 shows that live funds outperform defunct funds ("Graveyard funds") with a higher standard deviation on average. The graveyard funds also have slightly higher maximum and lower minimum returns than live funds, consistent with higher volatility of the defunct funds. In addition, Table 1.1 shows the need to separate the exit types. Graveyard funds are further broken into liquidated funds and funds that are alive but stopped reporting: "Not reporting funds". Liquidated funds have significantly lower mean monthly returns than funds that simply stopped reporting to the database. This underlines the fact that not all funds exit due to liquidation. The not reporting funds are also more positively skewed with lower kurtosis than liquidated funds. In turn, as underlined earlier, not all liquidations are indeed failures as reported in the literature. In line with this, Table 1.1 also reports descriptive statistics for failures and discretionary closures. Real failures have the lowest mean monthly return of 0.50% with the largest standard deviation of 6.91% and lowest skewness of 0.25. The discretionary failures have a mean return that is higher than that of the live funds of

1.52% but lower than funds that simply stop reporting. I find that on average 41.9% of CTAs reject the null hypothesis of normality at the 5% level. Malkiel and Saha (2005) find that both managed futures funds and global macro hedge funds do not reject the Jarque-Bera test of normality.[8]

1.3 Methodology

1.3.1 Risk Measures

Standard Deviation. For each month starting January 1994, I estimate standard deviation using 60 month rolling windows of previous returns. Where 60-month data is not available a minimum of 24 months is used.

In what follows the discussion here follows closely that in Liang and Park (2010).

SEM - Semi-deviation - this measure is similar to standard deviation except that it considers deviation from the mean only when it is negative.

$$SEM \equiv \sqrt{E\{min[(R-\mu),0]^2\}}, \tag{1.1}$$

where μ is the average return of the fund. SEM has been found to be a more accurate measure for assets with non-symmetric distributions, Estrada (2001).

[8]See Jarque and Bera(1980).

VaR - *Value-at-Risk* - is a risk measure widely used by portfolio managers which provides a single number for the risk of loss on a portfolio. This measure allows one to make a statement of the following form: We are (1-α) percent certain that we will not lose more than *VaR*(α,τ) dollars in τ days. Thus VaR uses two parameters: the horizon (τ), and the confidence level, (1-α). I use a 95% confidence level (α=0.05). The frequency of the data dictates the time horizon, which is monthly in this case. In particular, the VaR statistic can be defined as a one-sided confidence interval on a portfolio loss:

$$Prob[\Delta\widetilde{P}(\Delta t, \Delta\tilde{x}) > VaR] = 1 - \alpha, \tag{1.2}$$

where $\Delta\widetilde{P}(\Delta t, \Delta\tilde{x})$ is the change in the market value of the portfolio, as a function of the time horizon Δt and the vector of changes of random variables. This formulation shows that the distribution of the portfolio returns is key. Calculation of the true distribution is generally not feasible. VaR can be estimated using parametric techniques, however most assume normally distributed returns. The VaR measure under this normality assumption becomes:

$$\mathit{VaR\_Normal}(\alpha) = -(\mu + z(\alpha) \times \sigma) \tag{1.3}$$

VaR_CF - The Cornish-Fisher (1973) expansion (VaR_CF) considers higher moments in the return distribution such as skewness and kurtosis. It is possible to obtain an approximate representation of any distribution with known moments in terms of any known distribution, for example normal distribution. Thus the Cornish-Fisher expansion explicitly incorporates skewness and kurtosis, making it particularly suitable for use with CTA data. The equations below explicitly show the terms in the Cornish-Fisher

(1937) expansion.

$$\Omega(\alpha) = z(\alpha) + \frac{1}{6}(z(\alpha)^2 - 1)S + \frac{1}{24}(z(\alpha)^3 - 3z(\alpha))K - \frac{1}{36}(2z(\alpha)^3 - 5z(\alpha))S^2 \quad (1.4)$$

$$VaR\_CF(\alpha) = -(\mu + \Omega(\alpha) \times \sigma) \quad (1.5)$$

where μ is the average return, σ is the standard deviation, S is the skewness, K is the excess kurtosis of the past $24 - 60$ monthly returns of CTAs, $(1 - \alpha)$ is the confidence level, and $z(\alpha)$ is the critical value from the standard normal distribution.

ES - Expected Shortfall - Another measure of risk that is included in the analysis is the expected shortfall, ES. Artzner, Delbaen, Eber and Heath (1999) argue that ES has superior mathematical properties to VaR. Liang and Park (2007) formally test this for hedge funds and confirm that expected shortfall is better able to explain the cross-section of hedge funds. Unlike VaR, ES tells us how big the expected loss could be once VaR is breached. It is therefore more sensitive to the shape of the loss distribution in the tail of the distribution. ES is the conditional expected loss greater or equal to VaR, sometimes called conditional value at risk. It can be defined in terms of portfolio return instead of notional amount and is defined as follows:

$$\begin{aligned} ES_t(\alpha, \tau) &= -E_t\left[R_{t+\tau} | R_{t+\tau} \leq -VaR_t(\alpha, \tau)\right] \\ &= -\frac{\int_{v=-\infty}^{-VaR_t(\alpha,t)} v f_{R,t}(v) dv}{F_{R,t}[-VaR_t(\alpha, \tau)]} \\ &= -\frac{\int_{v=-\infty}^{-VaR_t(\alpha,t)} v f_{R,t}(v) dv}{\alpha} \end{aligned} \quad (1.6)$$

where $R_{t+\tau}$ denotes portfolio return during periods t and $t+\tau$, and $f_{R,t}$ is the conditional probability density function (PDF) of $R_{t+\tau}$. Here, $F_{R,t}$ denotes the conditional CDF of $R_{t+\tau}$ conditional on the information available at time t, $F^{-1}1_{R,t}$, and $1-\alpha$ is the confidence level. To compute 95% ES using the Cornish-Fisher expansion, one needs to compute 95% VaR_CF based on equation (1.4) and (1.5) and then search through the 60-month returns window to find all the returns that are below the calculated 95% VaR. The average of the obtained returns is ES_CF with a 95% confidence level. Alternative way is to use the analytical solution due to Christoffersen and Goncalves (2005). However, Liang and Park (2010) show that due to extreme skewness of some of the hedge funds the analytical solution is not very applicable.

TR - Tail Risk - Tail Risk is known as the possibility that an investment will move more than three standard deviations from the mean and this probability is greater than that shown by normal distribution. Tail risk arises for assets that do not follow normal distribution. In this context, tail risk is the standard deviation of the losses greater than VaR from the mean, or, more formally:

$$TR_t(\alpha,\tau) = \sqrt{E_t[(R_{t+\tau} - E_t(R_{t+\tau}))^2 | R_{t+\tau} \leq -VaR_t(\alpha,\tau)]} \tag{1.7}$$

Note that TR_CF denotes Tail Risk estimated using VaR_CF as a cut-off criteria.

Maximum Drawdown - Drawdown is any losing period during an investment record. It is defined as the percent retrenchment from an equity peak to an equity valley. A drawdown is in effect from the time an equity retrenchment begins until a new equity high is reached (i.e. In terms of time, a drawdown encompasses both the period from equity peak to equity valley (Length) and the time from the equity valley to a new equity high (Recovery). Maximum Drawdown is simply the largest percentage drawdown that has occurred in any investment data record. Diz (1999b) analyses the effect of various variables on the probability of survival of CTAs and includes maximum monthly drawdown as one of the covariates. He finds that the maximum monthly drawdown and the maximum time to recover from a drawdown as a percentage of a program's life is negatively related to survival. Baba and Goko (2009) explicitly model time varying drawdown in their survival model of hedge funds only and come to the same conclusion.

Maximum Drawdown relative to Standard Deviation - I also calculate drawdown relative to annualized standard deviation. Annualized standard deviation is given by:

$$St.Dev.Annualised = \left(\sqrt{ \left(\frac{\sum_{i=1}^{N} (R_i - \mu_R)^2}{N-1} \right)} \times 12 \right)^{\frac{1}{2}} \tag{1.8}$$

The proportion is calculated as:

$$= \frac{Max.Drawdown}{Std.Dev.Annuliased} \tag{1.9}$$

Once the drawdown reaches two times annualized standard deviation the fund is unlikely to survive.

1.3.2 Survival Analysis

Survival analysis is concerned with analyzing the probability and time until some event occurs. Such events are typically referred to as failures. In this context, failures are defined as financial distress of CTAs. In the literature the problem of hedge fund survival and variables that affect it is addressed by the use of hazard models. The underlying setting of these is as follows. If we denote T as a nonnegative continuous random variable representing time to failure of a CTA. The cumulative probability distribution is given by:

$$F(t) = Pr(T \leq t) \tag{1.10}$$

F(t) is also known in the literature as the *failure function*. An alternative formulation, which is at the core of the survival analysis, is the *survivor function*: an elapsed time since the entry to the state at time 0. This is given as:

$$S(t) = 1 - F(t) = Pr(T > t) \tag{1.11}$$

where t is time and the survival function represents the probability of a CTA surviving beyond time t.

The pdf is the slope of the failure function, *F(t)*:

$$f(t) = \lim_{\Delta t \to 0} \frac{P(t \leq T \leq t + \Delta t)}{\Delta t} = \frac{\partial F(t)}{\partial t} = -\frac{\partial S(t)}{\partial t} \tag{1.12}$$

Both the survivor function and failure function are probabilities. In particular, the survivor function, *S(t)* is a non-increasing continuous function of t with S(0)=1 and

$\lim_{t\to\infty}$F(t)=0. The survivor function increases toward zero as t goes to infinity. As such, the density function, *f(t)* is strictly non-negative but may be greater than one.

$$f(t) \geq 0 \tag{1.13}$$

The hazard function *h(t)*, known as the conditional failure rate, specifies the instantaneous rate at which failures occur in a given interval, conditional upon the fund surviving to the beginning of that interval. The *hazard function* is defined as:

$$\begin{aligned} h(t) &= \lim_{\Delta t \to 0} \frac{P(t \leq T < t + \Delta t | T \geq t)}{\Delta t} \\ &= \lim_{\Delta t \to 0} \frac{F(t + \Delta t) - F(t)}{\Delta t S(t)} = \frac{f(t)}{S(t)} = \frac{-dlnS(t)}{dt} \end{aligned} \tag{1.14}$$

where $P(\bullet|\bullet)$ denotes the conditional probability that an event will occur and *f(t)* denotes the probability density function associated with *F(t)*. The hazard function, therefore, fully specifies the distribution of t and subsequently the density and survivor functions. The only restriction on the hazard rate implied by the properties of these functions is that:

$$h(t) \geq 0 \tag{1.15}$$

Thus $\lambda(t)$ may be greater than one, in the similar way that *f(t)* may be greater than one. In fact there is a key relationship between these functions that underpins much of the survival analysis. Whatever the functional form for the hazard rate, $\lambda(t)$, one can derive the survivor function *S(t)*, failure function *F(t)* and integrated hazard rate *H(t)* from it. In particular from (11) and (13) we obtain:

$$\begin{aligned} h(t) &= \frac{f(t)}{S(t)} \\ &= \frac{f(t)}{1-F(t)} \\ &= \frac{-\partial[1-F(t)]/\partial t}{\partial t} \\ &= \frac{\partial{-ln}[1-F(t)]}{\partial t} \end{aligned} \tag{1.16}$$

Integrating both sides with respect to t and using *F(0)* $= 1$,

$$\begin{aligned} \int_0^t h(u)du &= -ln[1-F(t)]|_0^t \\ &= -ln[S(t)] \end{aligned} \tag{1.17}$$

Hence, the survivor function can be expressed in terms of hazard rate and subsequently the cumulative hazard:

$$\begin{aligned} S(t) &= exp\left(-\int_0^t h(u)du\right) \\ &= exp[-H(t)] \end{aligned} \tag{1.18}$$

The term *H(t)* is called *cumulative hazard function* and measures the total amount of risk that has accumulated up to time t whereas the hazard rate has units of $1/t$. Hazard functions have an advantage in that they have a convenient interpretation in the regression models of survival data of the effect of the coefficients. Once hazard rate is estimated, it is possible to then derive the survivor function using (1.18). Fundamental to this is an appropriate estimation of the hazard rate.

There are two types of model that can be used to analyze the survival data: duration models and discrete-time models. This study employs duration type models as they are better able to deal with the problem of right censoring. Right censoring is the term used to describe funds in the sample that have not failed during the observation period. These funds are the live funds of the database and funds that have been identified as having stopped reporting. Excluding such funds would lead to a downward bias of the survival time since live funds are also at risk during the sample and thus contribute information about the survival experience, Rouah (2005). Censoring, therefore occurs because there is no information on funds that do not experience failure during the period. An underlying assumption is that censoring is independent of the failure rates, and observations that have been censored do not have systematically higher or lower hazard rates that could essentially lead to biased coefficient estimates, Kalbfleisch and Prentice (2002). Also included in the censoring are the funds that have dropped out of the sample during the examination period for reasons other than failure, e.g. funds that have merged or restructured and thus ceased to report to the database, Ng (2008).

The survival function *S(t)* and the hazard function $h(t)$ can be estimated with the use of nonparametric univariate methods as well as parametric and semiparametric multivariate methods. Semiparametric methods are still parametric since the covariates are still assumed to take a certain form. The nonparametric methods, on the other hand, make no distributional assumptions and can handle right censoring. The Kaplan-Meier (1958) or the *product limit estimate* is an entirely nonparametric approach. Under the assumption of right censoring, let $t_1 < t_2 < t_3 < ... < t_j < ... < t_k < \infty$ represent observed sample survival times. Let d_j denote the number of funds that exit at each t_j and let m_j denote the number of censored funds at the same time interval. The risk set is then defined as the set of the durations:

$$n_i = \sum_{j \geq i}^{k} (m_j + d_j) \tag{1.19}$$

The proportion of funds that have survived to the first observed survival time, $\hat{S}(t_1)$ is simply one minus the number of failed funds divided by the total number at risk. Multiplying survival over all intervals yields the Kaplan-Meier survival estimator:

$$S(t) = \prod_{j|t_j<t} \left(1 - \frac{d_j}{n_j}\right) \tag{1.20}$$

The earlier discussion has shown how one can easily derive from *S(t)*, the hazard rate $\lambda(t)$ and the cumulative hazard rate *H(t).* These estimates, however, can only be derived at the dates at which failures occur and therefore the resulting survivor and integrated hazard functions are step functions. Since these are not easily differentiable, a smoothing kernel is used to derive the estimated hazard function. For the hazard curves, however, the Nelson-Aalen estimator has better small sample properties and is used to derive smoothed hazard curves.

$$\hat{H}t_j = \sum_{j|t_j<t} \left(\frac{d_j}{n_j}\right) \tag{1.21}$$

The most commonly used semiparametric model is Cox's (1972) model. This focuses on estimating the hazard function, $\lambda(t)$ and assumes that all the funds have a common baseline hazard rate $\lambda_0(t)$, but the method also assumes that the covariates have multiplicative effect and are able to shift the baseline hazard function. The method is widely used due to its computational feasibility. In its basic form the Cox (1972) function is:

$$\lambda_i(t; z_i) = \lambda_0(t)e^{z_i^T \beta}, \tag{1.22}$$

where z^T is the vector of the covariates for the ith CTA, and β is a vector of regression parameters. The model relates the effect of covariates on the hazard ratios. Cox (1972) proposed the use of partial likelihood to estimate the model which also eliminates the unknown baseline hazard rate and at the same time accounts for censored observations.[9]

The first to apply Cox's (1972) model to hedge funds were Brown, Goetzman and Park (2001). They found that funds with poor past performance and young funds have an increased risk of failure. Gregoriou (2002) finds that, apart from past returns, AUM and minimum investment also affect survival. For CTAs, the only study to apply Cox's (1972) model is that of Gregoriou, Hubner, Papageorgiou and Rouah (2005). In addition to past performance, volatility and assets under management, the authors also investigate the effect of minimum investment and management fees on survival. They find that management fees, in particular, have a negative effect on survival. The effect of risk, represented by standard deviation is particularly strong in their results and they document that Cox (1972) provides a good fit for their CTA data. Rouah (2005) analyses the survival of HFR hedge funds by using various exit types provided in the graveyard. Extending the Brown, Goetzman and Park (2001) model to multiple exit types allows the effect of the predictor variable to be assessed for each exit type separately. Rouah

[9] In this context censored observations are live funds in the database.

(2005) makes another contribution by allowing the covariates to be time dependent:

$$\lambda_j(t;\beta_j,Z(t)) = \lambda_{j0}(t)e^{z(t)^T\beta_j} \tag{1.23}$$

Treating explanatory variables as time dependent allows one to evaluate their impact on survival at each instant in the lifetime of funds, rather than just the last month. Thus Rouah (2005) finds that when volatility is treated as time dependent it increases the risk of liquidation and, furthermore, that persistent volatility is more important in predicting failure than short-term volatility. Brown, Goetzman and Park (2001) find that losing managers increases volatility in an attempt to bolster returns and this in turn may hasten funds' liquidation. Systematic funds are unlikely to increase volatility as the trading algorithms have set parameters and no human emotion. They are likely to be less volatile or have a more steady volatility. If systematic funds have controlled volatility the inclusion of risk measures is of particular interest as it may shed some light on the differences in survival between discretionary and systematic funds. Liang and Park (2010) incorporate calendar time into the analysis by using the counting process style input (CPSI) of Anderson and Gill (1982), which has a known importance for risk measures.

The following is a list of variables used in this study:

- *Risk measures*
- *Style effect* - I use several investment styles to control for variation in liquidation across various CTA styles. These are summarized in the appendix.
- *Performance* - The monthly average rate of return for the last year is used.

- *Size* - The monthly average AUM during the previous year is used.
- *Age* - The number of months a fund has been in existence.
- *Management fee*
- *Incentive fee*
- *HWM* - A dummy variable is used for funds with high watermark.

I do not include a lock-up provision as most CTAs rarely use them due to the liquidity of futures markets.

1.4 Empirical Results

1.4.1 CTA Attrition, Liquidation and Failure Rates

Earlier literature suggests that the survival of CTAs is lower than that of hedge funds. For example, both Liang (2004) and Getmansky, Lo and Mei (2004) found CTAs to have higher attrition rates than hedge funds (23.5% for CTAs versus 17% for hedge funds in Liang (2004), and 14.4% and 8.7% respectively in Getmansky, Lo and Mei (2004)). Brown, Goetzman and Park (2001) also found that CTAs had an average annual attrition of 20% for the 1990-2001 period, whereas hedge funds had a rate of only 15%. Other studies on CTAs only also support these results: Capocci (2005) and Fung and Hsieh (1997b) document attrition rates of 19.2% and 19% respectively. Although a lot of the previous literature indicates that CTAs have high attrition, Gregoriou et al.(2005) suggest that these studies do not take into account the extreme market events of August 1998 and September 2001 during which CTAs provided investors with downside protection since CTAs are found to have low correlation to equity portfolios, see Schneeweis, Spurgin and McCarthy (1996). A recent study by Xu et al. (2010) used a longer time frame to study attrition of both hedge funds and CTAs and found CTAs to have lower attrition than hedge funds. Looking at a longer time period that spans multiple crisis appears to even out and lower the attrition of CTAs.

Tables 1.2, 1.3 and 1.4 report annual frequency counts for funds entering and exiting the Live database and moving into the Graveyard. Table 1.2 shows attrition rate, liquidation and failure rates for all CTAs together whilst Tables 1.3 and 1.4 report the same information for systematic and discretionary funds respectively. Fung and Hsieh (1997b) do not include funds that enter and exit in the same year but this creates a downward bias in the estimated attrition rate. Truly liquidated funds are now separated from funds that are alive but stopped reporting which allows to calculate liquidation rate. Since investors are negatively affected by the failed funds rather than discretionary closures failure rate is of more interest to investors.

The average annual attrition rate across all funds for the period 1994-2009 is found to be 17.3%. There is evidence of variation across styles: systematic funds have an average attrition rate of 16.0%, discretionary 20.0% and options 18.6%. The options category should be treated with caution, however, as the sample is very small. Systematic funds appear to have the lowest attrition. The table below provides a brief summary comparing the results for attrition, liquidation and failure rates.

	Attrition Rate (%)	Liquidation Rate (%)	Failure Rate (%)
All funds:	17.3%	14.6%	11.1%
Systematic:	16.0%	13.8%	10.4%
Discretionary:	21.0%	16.3%	12.6%
Options:	18.5%	14.7%	10.6%

The attrition rate of all the funds is consistent with the previous literature Capocci (2005), Fung and Hsieh (1997b). The lower liquidation rates are intuitive because liquidation is a subset of attrition rate and excludes funds that are alive but have discontinued reporting to the database. Failure rate is a further subset of liquidation. The failure rates shown above are significantly lower than the attrition rates, but are not as low as the 3.1% reported for hedge funds in Liang and Park (2010) and the 3-5% reported in Rouah (2005). Interestingly, CTAs have a lower birth rate compared to hedge funds. The birth rate in this dataset across all CTAs is 17.8%, whilst Getmansky, Lo and Mei (2004) report a birth rate of 20.4% for hedge funds. On the other hand, discretionary funds have a birth rate of 19.0% which is close to the one reported for hedge funds. This is possibly because discretionary funds are similar to global macro hedge funds and are quite different to systematic CTAs. To set up a proper systematic CTA requires a lot of intensive research and model developing which serves as a significant barrier to entry to systematic CTAs, a feature that contributes to their lower liquidation rate.

The year-to-year attrition rates exhibit different patters within each category of funds. Across all CTAs the lowest attrition rate was 11.7% in 2003, with a failure rate of 7.9% in the same year. There is considerable variation in the attrition across the years, however. Attrition and failure rates start to decline at the beginning of 2000 until they rise again to an unprecedented levels (24.3%) in 2009. Discretionary CTAs have considerably larger attrition and failure rates, with levels climbing to 30.4% for attrition and 12.2% failure in 2009. This is much higher than the rates across systematic funds where both attrition and failure rates are fairly stable across the years with the highest rates, in 2009, of 21.4% and 8.3% respectively. Of note is that, contrary to the findings of Getmansky, Lo and Mei (2004) for hedge funds, the attrition and failure rates are lowest for systematic funds from 2000 to 2003. This period represents the bursting of the technology bubble, when many hedge funds experienced bad performance. CTAs have been documented by several studies to have performed particularly well during market downturns, hence the decline in their failure rates Fung and Hsieh (1997b), Edwards and Caglayan (2001).

Although the data shows relatively high attrition rates for CTAs, these estimates are inflated by the number of very small funds in the database. As shown in Figure 1.1, whereas 80% of CTA funds have assets below US$20 million, most of the assets of the CTA industry are managed by a very small number of funds. Table 1.5 shows attrition, liquidation and failure rates after excluding all funds with assets below US$1 million, US$10 million, US$20 million. As smaller funds are excluded, attrition, liquidation and failure rates drop, to the extent that, for systematic CTAs in particular, the failure rate approaches the 3% figure reported in Liang and Park (2010) for hedge funds. Yet this study used more extensive filters and included a larger number of failures than in Liang and Park's (2010) study. Excluding funds with assets less than US$20 million reduces the attrition rate to less than 10% with an even lower rate for systematic CTAs. Given that most hedge fund studies exclude funds with less than two years of data, which would exclude a lot of funds with small AUM, it is not surprising that previous research on hedge funds documented low attrition rates. Capocci (2005) included all the CTAs in his attrition analysis, hence a large attrition rate. It is likely that funds with assets below US$1 million are traders trading their own capital and do not constitute proper funds, yet the large number of these in the database tends to inflate the attrition rate. The results of this analysis suggest that the attrition of CTAs is not as high as previously thought: if small funds are excluded and, in particular, if funds with assets below US$1 million are excluded, the attrition rate drops to 11.7%. Liquidation and failure rates are even lower, with a failure rate approaching 3.4% for systematic CTAs, consistent with the practitioners' view as presented in Derman (2006).

1.4.2 Non-parametric Approach: The Kaplan-Meier Analysis of CTA Survival

This study begins its empirical analysis by measuring median survival times of CTAs for the period 1994-2009 using the Kaplan-Meier non-parametric approach. Such analysis can help prospective investors to select funds that are more likely to survive a long time and thus avoid liquidation. Panel A of Table 1.6 reports median survival times in months for the unfiltered database across the three main CTA categories: systematic, discretionary and options, as well as for three definitions of exit: all funds in the graveyard database, liquidated funds and failed funds only. Panel B shows the same results but for data that has been filtered to exclude funds than never reached US$5 million assets under management. This is a very basic filter that attempts to remove the large number of very small CTAs, a problem that was discussed in section 4.1. The table also shows the median survival times for large and small funds in each category and the respective p-value of the Log Rank test of equality between the two groups.

The results of Table 1.6 highlight an important difference between exit type; compared to the results for other exits, median survival is longest for failed funds. In fact, median survival also increases for liquidated funds, compared to using the entire graveyard, and further increases for failed funds. All exits comprises liquidated funds, merged funds, fraud, not reporting funds and funds that self-selected. Self-selected funds are defined as alive funds that no longer wish to report as they are closed to new investors. Not reporting funds are funds that are also alive but had to stop reporting for other reasons than capacity. For example, such funds may have stopped reporting because they now manage their own assets only, have not achieved NFA registration, are exempt, or other reasons not related to capacity. These funds, however, comprise only a tiny fraction of the total funds, namely just 60. Similarly, unlike hedge fund databases, the number of the self-selected funds is rather small, just 4% compared to 11% in Liang and Park (2010) and 10.7% in Fung et al. (2008), possibly because CTAs are unlikely to be as affected by capacity constraints as the other hedge fund strategies.[10] This study also finds a few fraudulent funds from various website filings. Table 1.6 Panel A shows that funds in the group "All exits" have a median survival of 4.17 years (50 months), a result similar to the 4.42 years found in Gregoriou et al. (2005), who used the entire graveyard in their analysis without applying any filters. For liquidated funds, median survival drops to 4.75 years across all funds and to 5.75 years for all failed funds. This suggests that CTAs can experience other types of exit besides failure and liquidation. Baba and Goko (2009) show different survival curves for different exit types of hedge funds which underlines the importance of sorting graveyard into various exits. Panel C gives an insight into these other types of exit and their effect on median survival times. Fraudulent funds have the shortest median survival of 2.33 years. Also, funds that are still alive but stop reporting due to capacity constraints or other reasons have a short median survival of 3 years, which has a downward impact on the median survival of all exits compared to liquidated funds only. This demonstrates that funds close fairly

[10] 99 out of 2446 funds are self selected.

quickly once they reach enough assets. The results are further confirmed in Figure 1.5 which shows survival curves by graveyard status together with corresponding smoothed hazard curves. Although Figure 1.5 does not include failed funds, since they form part of the liquidated funds, it clearly demonstrates that survival and hazard curves differ substantially across different exit types, with fraudulent funds having the lowest survival curve, a result that is consistent with Brown et al. (2009) who found that funds with high operational risks at the extreme have a half-life of less than 3.5 years.

Table 1.6 also indicates that filtering the database for very small funds that comprise a large share of the total number of funds has an effect on funds' half-life. The median survival across all exits is larger in Panel B than in Panel A: the median survival for all funds and all exit types increases to 5.7 years, to 6.4 years for all liquidated funds and to 8.9 years for all failed funds. Table 1.6 also reports on how survival time relates to strategy variation. Systematic funds have the longest survival compared to discretionary funds and options funds. This is invariant to the database used or exit type. In particular, the median survival of failed systematic funds that are above US$5 million is 9.5 years. For discretionary funds the median survival is 6.8 years. The superiority of systematic funds is invariant to whether the entire or the filtered database is used and persists across all exit types, liquidated and failed funds.

There are also significant differences between large and small funds. Large and small CTAs are defined as those with mean assets in the period 1994-2009 that are above and below the mean assets of all CTAs in the same strategy. Across all strategies, choosing a larger fund increases the survival of a CTA. For example, the median survival of systematic liquidated funds above US$5 million is 221 months for large funds and only 72 months for small funds. The difference is statistically significant at the 1% significance level. The difference between large and small funds is statistically significant across all strategies and all funds apart from options funds in the failed and liquidated category (Panel B). This is consistent with the findings in Table 1.5 that shows the attrition of larger funds dropping. Larger asset base is therefore associated with longevity.

Table 1.7 compares median survival across various strategies and two exit types, all exits and failures only, for 892 CTAs that were filtered using a dynamic AUM filter as proposed in Avramov, Barras and Kosowski (2010). The authors argue that few institutional investors wish to represent more than 10% of a fund's assets under management. According to the practitioner side, reported in L'habitant (2006), a typical number of funds held by a fund of funds is about 40. Therefore the dynamic AUM cutoff filter is equal to the minimum fund size such that a "typical" fund of funds does not breach the 10%-threshold.[11] Applying this filter, the resulting cutoff rises from $13 million in 1994 to $54 million in 2009. In comparison to Table 1.6, with a dynamic AUM filter applied, the median survival increases, reinforcing the contention that larger assets are associated with longevity. The p-value for the Log-Rank test is still significant across all funds and all exit types, indicating that there are still significant differences between large and small funds, despite the fact that the funds have been filtered by asset size. The median survival of all funds for all exits increased to 77 months (6.4 years) and to 130 months (10.8 years) for failed funds. Systematic funds again have the longest half-life across both exit types: 144 months for failed funds and 105 months for all exits, indicating that this is the strategy with the longest longevity. This result is further demonstrated in Figure 1.6 which shows a plot of survival and hazard curves for systematic and discretionary funds. The result also supports the earlier finding of Table 1.5

[11]The typical fund of funds is defined as a fund with an average AUM as measured by the fund of funds AUM in the database which on average invests into 50 CTAs.

where systematic CTAs were shown to have the lowest attrition and failure rates. This points to differences within different types of CTAs and supports the earlier argument that, contrary to previous studies that grouped all CTAs, it is better to analyze these funds by separating systematic and discretionary funds.

There are some variations with sub-strategies. Systematic trend-followers, led by short-term trend-followers have the highest median survival; a result further supported in Figure 1.7 which shows survival and hazard curves across different sub-strategies of CTAs for 892 failed funds. This result is consistent with Capocci (2005) and Gregriou et al. (2005) who argue that there are significant difference across CTA styles. Panel B demonstrates that an investor randomly selecting a newly launching systematic short-term trend-following fund can expect the fund to survive 12.7 years before liquidation and failure. Choosing a large fund in this category will further increase the survival to 14.3 years (172 months), whilst a small fund will survive 9.5 years. The difference is statistically and economically significant at 1%. On the other hand, an investor investing into a newly launching discretionary fundamental fund can expect the fund to survive for 7.8 years (93 months) before failing. These results are in sharp contrast to the median survival times reported in Gregoriou et al. (2005). There the authors report survival times that are significantly lower than in this study, with overall survival times of just 4.42 years. This is because their study used the entire graveyard as their definition of failure and therefore their results are only directly comparable to the results of Panel A in Table 1.6. Neither does their study filter out small funds from the sample which could further influence the results. Furthermore, unlike this study, the authors follow the strategy classification of BarclayHedge and therefore obtain very different results across CTA classifications. Accordingly, they find that systematic funds have the lowest median survival of only 3.33 years, whereas this study finds that systematic funds have the highest survival of 4.42 years,[12] even when using the unfiltered database and treating all exits as failures. The median survival time changes significantly with dynamic AUM filtering and using only failed funds, raising the median survival of systematic funds to 12 years (144 months). In fact, on this approach the entire ranking is reversed. In contrast to the approach of Gregoriou et al., Diz (1999b) uses Barclay Trading Group for the period 1975 to 1995 and finds that systematic traders have a greater probability of survival than discretionary. These results highlight the importance of different types of exits that need to be carefully accounted for together with the need for clear strategy definition that is yet to be conclusively established in the CTA space. Furthermore, they show that using the entire graveyard as definition of failure can impart a significant downward bias on medial survival. Standard deviation has no impact on media survival of CTAs which resonates with the results of Liang and Park (2010) for hedge funds.

Finally, Table 1.8 reports results of several Log-Rank tests for equality of survival functions for each sample stratified by the covariates of interest. This table is comparable to the one in Gregoriou et al. (2005) but is applied to the sample with a dynamic AUM filter and with failure only as the exit type. Similarly to Gregoriou et al. (2005) the results indicate that CTAs with above average mean return ($\geq 0.95\%$) survive longer as well as those with above average assets under management ($\geq$ \$103 million). Gregoriou et al. (2005), however, report lower survival times of 5.33 years and 6.16 years respectively in comparison to 14.67 years and 12.17 years for filtered failed funds in this study. Table 1.8 also reports that while funds with higher management fees and incentive fees survive longer, the difference in survival time is only statistically signifi-

[12] 53 months, from Panel A in Table VII

cant for performance fees. This is in contrast to Gregoriou et al. (2005) who find that management fees positively impact survival times. Similarly to Gregoriou et al. (2005), however, Table 1.8 reports no difference in survival when the sample is grouped by the standard deviation. Minimum purchase also has a very weak effect on survival times. The results indicate that the monthly return, average funds managed and performance fees have an important implication on the survival.

1.4.3 Cox Proportional Hazards Model

A Survival Analysis to Predict Attrition

In the remainder of the analysis the sample consisted of funds that were selected with a dynamic AUM filter - thus reducing the sample to 892 CTAs. Table 1.9 presents the results of fitting the Cox proportional hazards model of Gregoriou et al. (2005) and follows a conventional classification that defines failure as all exits to the graveyard. The first column is a parameter estimate and the second reports the associated hazard ratio, which is e^{β} for the covariate. Hazard ratio provides an easier interpretation of the level of a covariate's influence. For binary variables with values of 1 or 0, the hazard ratio can be interpreted as the ratio of hazard for those with a value of 1 to the estimated hazard for those with a value of 0, after controlling for other covariates. For quantitative variables, the hazard ratio estimate needs to subtract 1 and multiply by 100 which gives a percentage change in the hazard for each unit increase in the covariate, controlling for other variables. According to Allison (1995) a simple interpretation of the estimated hazard ratio is that a hazard ratio greater than one implies a negative effect of the covariate on survival, while a hazard ratio less than one indicates a protective effect of the covariate. The corresponding p-value reports the p-value for the Wald test of the null hypothesis that each coefficient is equal to zero. The results indicate that only three variables have a significant effect on survival: mean monthly return over the entire life of the fund, average millions managed and management fees. It is found that higher average monthly returns as well as assets under management are protective whereas higher management fees are not. The results closely mirror the findings of Gregoriou et al. (2005) even though the sample in this study was filtered by asset size. Specifically, the hazard ratio of the mean return is 0.838, indicating that an increase in the monthly return of 1% leads to 16.2% reduction in the likelihood of failure. The protective effect of the AUM is marginal. However, every percentage point increase in the management fee increases the likelihood of failure by 15.2%. The goodness of fit provided by the Likelihood ratio test and the Global Wald test, both are significant, and lends support to the accuracy of the functional form of the model.

For comparison, Table 1.10 reports the results of the Liang and Park (2010) LP model, with failure defined as exit to the graveyard. Compared to the LP model, where all risk measures are significant when they are the only explanatory variables, Panel A shows that only standard deviation and expected shortfall are significant risk measures. When other explanatory variables are added to the model, Panel B, standard deviation loses its significance but value at risk becomes significant at 10%. This supports the earlier results of Table 1.9 that standard deviation is not a useful measure of CTA survival. The hazard ratios of the VAR and ES are below one, which is not intuitive since it implies that higher risk funds have lower hazards. This strengthens the argument of

Rouah (2005) that the effect of the covariates becomes blurred when all the graveyard funds are regarded as failures. With regard to the impact of the other variables, Table 1.10 shows that only standard deviation of the AUM, leverage, HWM and a dummy variable for discretionary style are significant at the 1% significance level. Interestingly, the hazard ratio of leverage is protective. Baba and Goko (2009) conducted a Tobit analysis with mean leverage as the dependent variable. They found that funds with high mean leverage also tended to have a larger AUM, a high water mark and a longer redemption period. These factors alone can lower the hazard ratios. The hazard ratio of high water mark in Table 1.10 is above one, indicating that CTAs with high water mark have increased risk of failure by as much as 60%, which is contrary to the results in Liang and Park (2010) who find HWM to be protective. Rouah (2005) also finds that HWM increases the risk of failure. The effect of high watermark on hedge fund survival remains unclear with different authors presenting different results. Rouah (2005), Ng (2008) and Lee (2010) all used the HFR database to study hedge fund survival and each found that HWM tended to increase failure, whereas Liang and Park (2010) and Baba and Goko (2010) analysed hedge fund survival using the TASS database and found that HWM is protective. The authors argue that the HWM facilitates more stable fund management as well as serves a signal quality for good managers. Liang and Park (2010) also cite Aragon and Qian (2005) who argue that HWM lowers existing investors' marginal cost of staying in the fund following its poor performance and hence allows fund managers to avoid liquidation by keeping its investors. Liang (2000), Brown, Goetzmann and Ibbotson (1999) and Rouah (2005), on the other hand, suggest that once the fund incurs large losses it is difficult for the manager to recuperate them and attain its high water mark and that this increases the incentive to liquidate. Gregoriou et al. (2005) do not include HWM in their model therefore it is impossible to obtain a direct comparison for this study. It is more likely, however, that the effect of HWM on CTA survival is negative, given the significance and the size of the hazard ratio.

Table 1.10 also shows that there are some style effects: discretionary funds have a higher hazard rate relative to systematic funds. Investing into a discretionary fund entails a hazard rate 37% higher than in systematic CTAs. The explanatory power of the mean return and mean AUM in the last year of a fund's life is weak, indicating the need for separating exit types. In addition to reporting the significance of the hazard ratios, Table 1.10 also reports "Rho", which is a slope estimate for each variable of the scaled Schoenfeld (1982) residuals against time. Under the null hypothesis of proportional hazards, the curve is expected to have a zero slope, thus rejection of the null hypothesis indicates a deviation from the proportional-hazards assumption. The Global Ph Wald test is a Wald statistic that tests whether all the covariates jointly satisfy the proportional hazard assumption, i.e. model specification. Apart from the model with ES as the risk measure, the global Wald test shows that the proportional hazards assumption is rejected as a whole at the 1% significance level, whilst only one variable, standard deviation of AUM, violates it.

A Survival Analysis to Predict Liquidation

The graveyard contains different types of exits, as reported in Table 1.6: liquidated funds, funds that are alive but stopped reporting due to capacity constraints or simply self-selected funds. Rouah (2005) argues that only liquidated funds should be used in the survival analysis in order to avoid blurring the effect of predictor variables. Table

1.11 reports the results of fitting the LP Cox proportional hazards model on liquidated funds only, that is the number of failed funds reduces to 441 from 529 and other types of exit are treated as censored. This model shows a marginal improvement in that both mean return and mean AUM become significant at 1%, however neither satisfy the proportional hazards assumption. The effect of risk measures in the univariate and multivariate models remains unchanged. This is similar to the results of Liang and Park (2010) who find that a model with liquidated funds produced misleading estimates. In what follows, therefore, the analysis concentrates only on failed funds identified with performance and AUM filters as discussed previously.

A Survival Analysis to Predict Failure

As discussed above, using liquidated funds is still not very informative in defining failure since many funds liquidate for reasons other than bad performance, e.g. merging with another fund. The remainder of the analysis, therefore, concentrates on the failed funds only. Table 1.12 shows several model specifications for failed funds with fixed covariates only. For comparison purposes, specification (i) includes the same variables as in the Gregoriou et al. (2005) model but applied to failed funds only. In contrast to Table 1.6, where all exits were treated as failure, Table 1.12 shows that the standard deviation over the entire life of the fund is now significant at 1% with a hazard ratio above one. Management fee is still significant and increases the likelihood of failure. The second specification adds skewness, kurtosis, winning ratio,[13] standard deviation of AUM over entire life of the fund, whether the fund has a hurdle rate, employs leverage,

[13]The number of months with a positive return to the total number months.

HWM and dummy variables for investment style. Skewness and kurtosis are significant at 5% and 10% respectively as well as the volatility of assets, leverage and the dummy for discretionary style.[14] The effect of skewness is protective: a unit increase in the skewness decreases the hazard rate of the fund by 14%. One would expect the survival to be positively related to the first and third moments and negatively to the second and fourth moments. Contrary to this expectation, however, the coefficient on kurtosis is negative indicating that it aids in survival. The effect is, however, marginal and the covariate is not significant in specification (iii). The effect of the winning ratio is to decrease the hazard rate of the fund whilst management fee increases the hazard rate. Similar to previous results, leverage is protective and discretionary funds are 57% more likely to fail than systematic ones. The hurdle rate is insignificant and is not included in the remaining specifications due to its incomplete data.

Specification (iii) further adds maximum drawdown over the entire life of the fund. Similar to the finding of Diz (1999b), this variable is highly significant and increases the hazard rate by 5% for every percentage increase in the drawdown. The hazard ratio of the winning ratio decreases to 0.08 at 1% significance level. The interpretation needs care, however, as the win ratio is the number of positive returns over the total number of returns and is therefore between 0 and 1, hence even a slight increase in this number can dramatically increase the estimated survival. In the final specification in Table 1.12 maximum drawdown is replaced by maximum drawdown relative to standard deviation. It shows that once maximum drawdown reaches three times annualized standard deviation the hazard rate increases by as much as 213%. If the drawdown is within two

[14] The dummy variable for systematic style was removed to avoid perfect multicollinearity in the estimation process. The coefficient of the other two strategy dummies represents the incremental change in hazard as compared to the default case.

standard deviations, the effect is protective, but above two standard deviations the fund is at risk of failure. The effect of HWM is significant in this model - funds with high water mark provision have an increased risk of failure by as much as 51% relative to funds without it. The effect of discretionary funds is unchanged, but the hazard ratio of the options funds becomes significant at 5% and demonstrates an increased hazard rate of the options funds relative to systematic ones.

Table 1.13 compares the five risk measures in terms of predicting the "real failure" of CTAs by using Liang and Park's (2010) model. Standard deviation remains an insignificant risk measure but semideviation, ES and TR each become significant. In particular, the effect of semideviation is to increase the hazard rate by 5%, whilst TR increases the hazard rate by 2%. The effect of ES remains unclear, however, since the hazard ratio is marginally below one. Mean return is found to be a highly significant covariate at the 1% level with a hazard ratio of 0.84, implying that high return funds have a lower hazard rate of failure. The fund size, as represented by the mean assets under management over the entire life of the fund, is significant at 1%, however the effect on survival is negligible. In addition this variable has a significant Rho, indicating that it violates the proportionality assumption. In fact both mean AUM and standard deviation of AUM violate the proportionality assumption. The previous studies of Ng (2008) and Lee (2010) included fund size as the natural logarithm of the fund's assets under management at the last month. The authors argue that the effect of the fund size on the duration is non-linear. One way to test this is to use the Martingale residuals to test for the best functional form of the covariate. The goal is to determine the best functional form that will result in an approximately straight curve of the martingale residuals against the covariate. In unreported tests I plot mean AUM against martingale residuals and log AUM against martingale residuals. The log transformation of the recent AUM yields a linear plot against martingale residuals, indicating a better fit. Given this result, I use natural logarithm of fund's assets under management at the last month rather than just assets under management in the survival model.

Table 1.14 extends Liang and Park's (2010) model by including a larger set of covariates than were previously tested in the base model as well as replacing mean AUM with the log of the last month AUM. In addition, Drawdown/STD is added as another risk measure. The most significant covariates, at 1% level, are mean return, fund size represented by the log of last month AUM, standard deviation of the AUM, a dummy for discretionary strategy and leverage. The protective effect of the mean return relative to previous models increases with an increase in mean return over the entire life of the fund resulting in a decrease in the hazard rate of 43%. The effect of fund size is also much stronger now with one unit increase in size reducing the hazard rate by 15%. The effect of standard deviation of AUM is negligible and both variables still show the rejection of the proportionality assumption with significant Rho. The way to circumvent this issue is by introducing these variables as time varying. Table 1.15 introduces AUM as a time-varying variable. I also introduce another variable, asset flow, Flow(t). Following Agarwal, Daniel and Naik (2009) monthly flow is defined as:

$$DollarFlow_{i,m} = AUM_{i,m} - AUM_{i,m-1}\left(1 + Return_{i,m}\right) \tag{1.24}$$

which is then scaled by the previous month's assets under management as in Sirri and Tuffano (1998) to obtain:

$$Flow_{i,m} = \frac{DollarFlow_{i,m}}{AUM_{i,m-1}} \tag{1.25}$$

Baba and Goko (2009) are the first to include a flow variable in the survival analysis which they justify by the return-chasing behaviour of investors, where investors flock to funds with good recent performance and withdraw funds from poorly performing funds (Chan et al. 2006). Agarwal et al. (2009) also document that money flows chase good recent performance and find that this relationship is in fact convex. However, they also find that larger funds with greater inflows are associated with poorer future performance underlining that hedge funds face diminishing returns to scale. Baba and Goko (2009) find the effect of Flow to be protective, i.e. recent inflows contribute to lower liquidation probabilities. Table 1.15 shows that whilst the effect of time-varying AUM is significant, the effect on survival is marginal whereas the protective effect of Flow is significant at 1% and is indeed much stronger than documented in Baba and Goko (2009), with a hazard ratio of 0.12. The effect of other variables seems to be unchanged: mean return, skewness, winning ratio, management fee and leverage all remain significant. HWM is no longer significant, whilst the incentive fee and minimum investment also remain insignificant. With the inclusion of time-varying AUM and Flow, SEM, ES and TR remain significant and VAR gains significance at 10%. The Likelihood ratio increases to 289.10 compared to 199.02 in Table 1.14 indicating an overall improvement in the model. Finally Table 1.16 adds ten dummy variables of which the eleven's strategy, Fundamental and Technical, was removed to avoid perfect multicollinearity in the estimation process.[15] The coefficient of the other ten strategies represent the incremental change in the hazard as compared to the default case, the fundamental and technical strategy. For example, the hazard ratio of short-term trend followers is 0.41, meaning it is 59% less likely to fail than discretionary CTAs employing a fundamental and technical

[15]Table 1.16 presents only the results for standard deviation, TR and drawdown/STD. The results of the model with the remaining risk measures are omitted to save space.

approach. The results indicate that only a few strategies are significant at the 1% level: short-term and medium-term trend followers. The coefficient on discretionary CTAs with a fundamental approach is significant in the models with TR and Drawdown/STD as risk measures, and systematic counter trend funds are 150% more likely fail than the default strategy. This is easy to understand since it is a rather difficult strategy to implement, as evidenced by the small number of counter trend funds.

Of particular interest in the above is the negative relationship between management fee and survival. The results across all tables demonstrate that, on average, an increase in management fee leads to an approximately 15% increase in the hazard rate. This is similar to the result in Gregoriou et al. (2005) but the effect is stronger for failed funds only. Baba and Goko (2009), however, find that the effect is reversed for hedge funds where management fee is protective whilst incentive fee is not. HWM becomes insignificant when time-varying AUM and Flow are added to the model.

1.4.4 Robustness Checks

In unreported results I test to see if my results are affected by changes in the confidence level of the risk measures or the use of different estimation models.

Changing the confidence level of the risk measures

The results above are further examined to determine if they are affected by the confidence level chosen to calculate VAR, ES and TR. Current results present a 95% confidence level. The results at the 99% confidence level are not much different to the results presented earlier. Standard deviation still appears to be insignificant in predicting real failure whilst SEM, ES and TR are significant at the 5% level.

The Probit Model

Malkiel and Saha (2005) and Brown et al. (2001) use a probit model to estimate the effect of variables on hedge fund survival. Using a probit model on the 817 funds for failure and attrition shows that results are not dissimilar to the Cox (1972) model. Standard deviation is still less efficient at predicting survival than other risk measures.

1.5 Conclusion

This chapter has analyzed the factors affecting CTA survival. It included a wide range of variables with particular emphasis on various downside risk measures as well as AUM and capital flows. In addition, it has offered an improvement in methodology when compared to previous studies on CTA survival. In contrast to previous survival analyses that incorporated only fixed covariates, this study included time varying covariates which allowed to evaluate their impact at each instant of a fund's lifetime rather than during the entire lifetime or the last 12 months. This study also adopted a novel CTA strategy classification that allowed for interesting comparisons between discretionary and systematic CTAs. Finally, it has taken into account the different exit types that CTAs can experience. It used a combination of various filters and hand-collected information to determine exit types. Further, an updated filtering methodology was proposed to screen for failed funds among CTAs. Based on this extensive data collection, the attrition rate and factors affecting CTA survival are investigated.

The main results demonstrate that the entire graveyard is a poor measure of CTA failure and it is therefore important to account for different exit types. Whilst attrition of CTAs is as high as 17.8%, similar to the rate for all hedge funds, the average percentage of liquidated funds is lower at 14.6%. However, once the real failures among the liquidated funds are distinguished, the rate drops to 11.1% suggesting that there are many discretionary liquidations that are not damaging to investors. As such this study develops filters to discriminate between failed funds. It also finds that the CTA database contains a large number of small funds with assets that are less than US$20 million. Institutional investors are unlikely to invest into such small funds and if they are removed from the sample the real failure rate drops to 3.9%, which is comparable to the failure rate reported for hedge funds. The failure rate for CTAs is therefore not as high as previously thought. Systematic CTAs are also found to have a lower failure rate than discretionary ones, 3.4% vs. 5.8%. This study also demonstrates that the attrition rate during the 2008 financial crisis climbed to an unprecedented level.

Further, the median survival time of large failed funds is found to be 10.8 years, which is higher than the previously reported median survival of 4.42 years in Gregoriou et al. (2005) and of 2 years reported in Brown et al. (2001). Spurgin (1999) has used the MAR CTA database over a shorter period and reports a survival time of approximately 5 years. My results show that an average systematic CTA has a median survival of 12 years compared to 8.33 years for a failed discretionary fund. Assets under management have an effect on survival as well, with larger funds having significantly higher median survival times when compared to smaller funds.

Using Cox's (1972) model with time-varying covariates the results show that standard deviation is not a good risk measure in terms of predicting CTA failure. Measures such as SEM and TR as well as maximum drawdown are better able to account for non-normality of CTA returns. Apart from variables such as performance and assets under management, asset flows into the funds have a positive effect on CTA survival. Funds that experience significant asset outflows have a higher chance of liquidation. Contrary to the findings of Liang and Park (2010) for hedge funds, the presence of a high water mark has a negative effect on CTA survival. Management fees increase the probability of failure whilst leverage has a protective effect. The effect of leverage could possibly be explained by the findings of Brown et al. (2009) as further discussed in Brown, Goetzmann, Liang and Schwarz (forthcoming), who find that funds with higher operational risks are less able to raise leverage since prime brokers and lenders are less willing to lend to funds that they perceive as risky. Conversely, funds that are more able to borrow may have less operational risk and thus lower liquidation probabilities. The results also show that funds with lower skewness, lower winning ratio and higher maximum drawdown have higher failure rates. Finally, there are important differences across CTA styles, with systematic CTAs and in particular systematic trend-followers experiencing lower hazard rates than any other strategy and these should therefore be favoured by investors.

1.6 Appendix

SYSTEMATIC - funds that employ purely systematic approach to trading, utilizing computer models that are mainly based on technical analysis of the market data and fundamental economic data. Trading can be diversified across many markets, including foreign exchange, interest rates, commodity, bond and equity markets. Manager intervention is limited. The core of systematic trading lies in strict management of volatility. *"Diversified program is a diversified portfolio of more than 120 international futures and forwards markets employing a computer based system. The system has been developed based on the basis of a sophisticated statistical analysis of past price movements and seeks to profit from the tendency of the markets to trend." Winton Capital Management, Ltd.*

Trend-following - by far the most represented strategy among systematic funds. This is a strategy that tries to take advantage of price movements in a systematic way and aims to work on the market trend, taking benefit from both up markets and down markets. *"Bluetrend fund is a systematic, trend-following black box fund, which trades on a 24 hour cycle and seeks to successfully identify trends." BlueCrest Capital Mgmt, LLP.*

Trend-following - Short-term - Systematic trend-follower with a short-term time frame of anything from intra-day trading up to one week.

Trend-following - Medium-term - Systematic trend-follower with a medium-term time frame of anything from one week to 30 days. *"Rotella Sirius Fund, LLC utilizes a multi-model approach targeting medium-term and long-term trends* *in global commodity, interest rate, currency and equity index markets. Sirius's average holding period is 25-50 days."*

Trend-following - Long-term - Systematic trend-follower with a long-term time frame from one month to several months.

Pattern Recognition - Systematic trading that bases its approach on statistical pattern recognition in a variety of markets, utilizing a particular field of computer science concerned with recognizing patterns. *"The trader exploits non-random price behaviour by quantitative analysis of price patterns. Its approach is entirely systematic. The systems are applied to more than 100 different product-market-combinations. Advanced correlation analysis safeguards portfolio balance." Transtrend.*

Spread/Relative Value - a systematic approach to arbitrage and relative value trading. Relative Value Arbitrage is a market neutral strategy that seeks to exploit pricing inefficiencies between related securities and markets, including equities, options, debt and futures. Managers tend to use mathematical models and technical analysis.

Counter Trend - systematic trading that takes advantage of price movements by adopting a contrarian approach to the trends. *"The Financials Program employs a quantitative, primarily contrarian, short-term strategy. RGNCM'S method captures changes in the psychology of market participants and has been particularly successful during volatile and declining equity and fixed income markets" R.G. Niederhoffer Capital Management.*

DISCRETIONARY - whereas systematic trading uses a fixed set of rules to determine trade entries and direction, the discretionary trader is not bound by any rules. In essence the trader uses his own judgement and evaluation of the market indicators, fundamental information, etc. to determine the value of the indicator and decides the point of entry, size of investment and level of risk taking.

Fundamental - discretionary trading that focuses on the analysis of fundamentals to inform investment decisions. Programs may focus on one market only or diversified markets. *"Albion utilizes a fundamental based discretionary approach to trade the major currencies." Albion Currency Advisors, Ltd*

Technical - discretionary trading that uses technical analysis, such as charts and price patterns, with most trading executed by the manager. Some funds may utilize computer based systems to look for price patterns but ultimately all the trading is executed by the manager.

Fundamental and Technical - a mixture of fundamental and technical analyses with manager discretion.

Discretionary Spread/RV - exploiting arbitrage opportunities with manager discretion.

OPTIONS STRATEGIES

Options Writing - programs that rely on selling or writing options.

Options Other - programs that utilize options trading other than selling. *"Reflects the performance of the Options Program - an intermediate term market neutral anti-trend following approach combining 60% fundamental and 40% technical*

analysis to trade U.S. fixed income and equity options" Analytic TSA Global Asset Mgmt, Inc.

All CTAs	**2446**
Systematic	**1511**
Trend-Followers	1263
Short-Term	331
Medium-Term	780
Long-Term	152
Pattern Recognition	96
Spread/Relative Value	128
Counter Trend	24
Discretionary	**747**
Fundamental & Technical	253
Fundamental	136
Technical	284
Spread/Relative Value	74
Options	**188**
Options Writing	113
Options Other	75

Table 1.1: **Summary Statistics**

Table 1.1 shows the number of observations *(N)*, mean values of sample average, standard deviation, skewness and kurtosis of individual CTA returns. The data is from the BarclayHedge database for the sample period from January 1994 to December 2009. The table also shows the percentage of CTA funds that reject the Jarque-Bera *(JB)* test of normality at the significance of 1%. The JB statistic has χ^2 distribution.

Drop Reasons	No. of Funds	Mean return (%)	Std. Dev. (%)	Skewness	Kurtosis	Min return (%)	Max return (%)	JB test of Normality (%)
Live funds	696	1.19	5.36	0.31	2.86	-11.80	18.23	45.11
Graveyard funds	1750	0.93	6.38	0.34	2.51	-13.01	18.78	40.57
Not reporting funds	265	1.93	5.99	0.41	2.23	-10.62	18.53	39.25
Liquidated funds	1485	0.76	6.45	0.33	2.56	-13.45	18.83	40.81
Discretionary	352	1.52	5.06	0.49	2.64	-8.94	16.76	43.18
Failures	1133	0.50	6.91	0.25	2.54	-14.95	19.52	40.07
All funds	2446	1.01	6.09	0.33	2.61	-12.67	18.23	41.9

Table 1.2: **Attrition, Liquidation and Failure Rate of CTAs**

Table 1.2 compares attrition, liquidation and failure rates across all CTAs. The data is from the BarclayHedge database for the sample period from January 1994 to December 2009. Attrition means all funds that are moved from the Live database into the Graveyard database. Liquidation rate includes all the funds that have liquidated as defined using several criteria. Failure is the real failure of those liquidated funds that have not experienced liquidation for discretionary reasons.

Year	Year Start	Entry	Exit	Stopped Reporting	Liquidated	Failure	Year End	Birth Rate	Liquidation Rate	Failure Rate	Attrition Rate
1993							663				
1994	663	113	111	8	103	84	665	17.0%	15.5%	12.7%	16.7%
1995	665	113	131	14	117	92	647	17.0%	17.6%	13.8%	19.7%
1996	647	101	133	13	120	92	615	15.6%	18.5%	14.2%	20.6%
1997	615	89	120	12	107	78	584	14.5%	17.4%	12.7%	19.5%
1998	584	91	104	11	93	63	571	15.6%	15.9%	10.8%	17.8%
1999	571	116	102	9	93	72	585	20.3%	16.3%	12.6%	17.9%
2000	585	83	103	7	96	68	565	14.2%	16.4%	11.6%	17.6%
2001	565	85	84	11	72	56	566	15.0%	12.7%	9.9%	14.9%
2002	566	126	69	5	63	50	623	22.3%	11.1%	8.8%	12.2%
2003	623	135	73	10	63	49	685	21.7%	10.1%	7.9%	11.7%
2004	685	162	86	7	79	57	761	23.6%	11.5%	8.3%	12.6%
2005	761	187	119	13	106	87	829	24.6%	13.9%	11.4%	15.6%
2006	829	178	147	28	119	99	860	21.5%	14.4%	11.9%	17.7%
2007	860	161	147	27	120	97	874	18.7%	14.0%	11.3%	17.1%
2008	874	131	179	40	138	85	826	15.0%	15.8%	9.7%	20.5%
2009	826	64	201	46	107	83	689	7.7%	13.0%	10.0%	24.3%
Total		**1935**	**1909**	**261**	**1596**	**1212**	**Average**	**17.8%**	**14.6%**	**11.1%**	**17.3%**

Table 1.3: **Attrition, Liquidation and Failure Rate of Systematic CTAs**

Table 1.3 compares attrition, liquidation and failure rates across Systematic CTAs. The data is from the BarclayHedge database for the sample period from January 1994 to December 2009. Attrition means all funds that are moved from the Live database into the Graveyard database. Liquidation rate includes all the funds that have liquidated as defined using several criteria. Failure is the real failure of the liquidated funds that have not experienced liquidation for discretionary reasons.

Year	Year Start	Entry	Exit	Stopped Reporting	Liquidated	Failure	Year End	Birth Rate	Liquidation Rate	Failure Rate	Attrition Rate
1993							410				
1994	410	60	55	5	50	42	415	14.6%	12.2%	10.2%	13.4%
1995	415	74	81	8	73	58	408	17.8%	17.6%	14.0%	19.5%
1996	408	64	73	8	65	50	399	15.7%	15.9%	12.3%	17.9%
1997	399	65	62	6	56	42	402	16.3%	14.0%	10.5%	15.5%
1998	402	67	68	9	59	38	401	16.7%	14.7%	9.5%	16.9%
1999	401	84	73	7	66	52	412	20.9%	16.5%	13.0%	18.2%
2000	412	47	66	1	65	45	393	11.4%	15.8%	10.9%	16.0%
2001	393	69	50	3	47	34	412	17.6%	12.0%	8.7%	12.7%
2002	412	82	48	1	46	36	446	19.9%	11.2%	8.7%	11.7%
2003	446	88	55	8	47	37	479	19.7%	10.5%	8.3%	12.3%
2004	479	110	56	2	54	40	533	23.0%	11.3%	8.4%	11.7%
2005	533	124	87	8	79	65	570	23.3%	14.8%	12.2%	16.3%
2006	570	97	111	21	90	74	556	17.0%	15.8%	13.0%	19.5%
2007	556	83	85	12	73	57	554	14.9%	13.1%	10.3%	15.3%
2008	554	62	97	22	75	50	519	11.2%	13.5%	9.0%	17.5%
2009	519	26	111	19	60	43	434	5.0%	11.6%	8.3%	21.4%
Total		**1202**	**1178**	**140**	**1005**	**763**	**Average**	**16.6%**	**13.8%**	**10.4%**	**16.0%**

Table 1.4: **Attrition, Liquidation and Failure Rate of Discretionary CTAs**

Table 1.4 compares attrition, liquidation and failure rates across Discretionary CTAs. The data is from the BarclayHedge database for the sample period from January 1994 to December 2009. Attrition means all funds that are moved from the Live database into the Graveyard database. Liquidation rate includes all the funds that have liquidated as defined using several criteria. Failure is the real failure of the liquidated funds that have not experienced liquidation for discretionary reasons.

Year	Year Start	Entry	Exit	Stopped Reporting	Liquidated	Failure	Year End	Birth Rate	Liquidation Rate	Failure Rate	Attrition Rate
1993							244				
1994	244	49	54	3	51	40	239	20.1%	20.9%	16.4%	22.1%
1995	239	37	49	6	43	34	227	15.5%	18.0%	14.2%	20.5%
1996	227	31	55	4	51	38	203	13.7%	22.5%	16.7%	24.2%
1997	203	20	53	4	48	34	170	9.9%	23.6%	16.7%	26.1%
1998	170	20	33	2	31	24	157	11.8%	18.2%	14.1%	19.4%
1999	157	26	29	2	27	20	154	16.6%	17.2%	12.7%	18.5%
2000	154	25	34	5	29	21	145	16.2%	18.8%	13.6%	22.1%
2001	145	9	31	7	23	20	123	6.2%	15.9%	13.8%	21.4%
2002	123	39	19	4	15	12	143	31.7%	12.2%	9.8%	15.4%
2003	143	34	12	1	11	8	165	23.8%	7.7%	5.6%	8.4%
2004	165	40	25	4	21	16	180	24.2%	12.7%	9.7%	15.2%
2005	180	41	30	5	25	21	191	22.8%	13.9%	11.7%	16.7%
2006	191	66	27	5	22	21	230	34.6%	11.5%	11.0%	14.1%
2007	230	60	52	14	38	33	238	26.1%	16.5%	14.3%	22.6%
2008	238	49	50	11	38	20	237	20.6%	16.0%	8.4%	21.0%
2009	237	25	72	24	35	29	190	10.5%	14.8%	12.2%	30.4%
Total		**571**	**625**	**101**	**508**	**391**	**Average**	**19.0%**	**16.3%**	**12.6%**	**21.0%**

Table 1.5: **Attrition, Liquidation and Failure Rate Across Styles by AUM**

Table 1.5 compares attrition, liquidation and failure rates across CTA styles. The data is from the BarclayHedge database for the sample period from January 1994 to December 2009. Attrition means all funds that are moved from the Live database into the Graveyard database. Liquidation rate includes all the funds that have liquidated as defined using several criteria. Failure is the real failure of the liquidated funds that have not experienced liquidation for discretionary reasons.

CTA Style	Birth Rate	Attrition Rate	Liquidation Rate	Failure Rate
		All funds		
All CTAs	17.8%	17.3%	14.6%	11.1%
Discretionary	19.0%	19.9%	16.3%	12.6%
Systematic	17.8%	16.0%	13.8%	10.4%
Excluding funds with AUM less than US$1 million.				
All CTAs	16.4%	14.1%	11.7%	8.6%
Discretionary	17.5%	16.6%	13.4%	10.3%
Systematic	15.4%	13.1%	11.0%	8.0%
Excluding funds with AUM less than US$10 million.				
All CTAs	14.7%	8.5%	6.8%	4.6%
Discretionary	16.5%	10.8%	8.3%	5.9%
Systematic	13.4%	7.8%	6.3%	4.1%
Excluding funds with AUM less than US$20 million.				
All CTAs	14.6%	8.2%	6.5%	3.9%
Discretionary	16.3%	10.3%	7.9%	5.8%
Systematic	13.3%	7.5%	6.0%	3.4%

Table 1.6: **Kaplan-Meier Estimated Median Survival Times (Half-Life) by Strategy and Exit Type**

Table 1.6 reports Kaplan-Meier median survival time in months along with the standard error (S.E.). Large and small funds are those CTAs that had mean assets for the period January 1994 to December 2009 that were above or below the mean assets of all funds in the same strategy. The Log-Rank p-value is for the Log-Rank test for equality of the survival functions of the large funds and small funds groups. Panel A shows survival times for three different exit types for the entire database without AUM filters. Panel B shows the survival times for the database that contains funds filtered above US$5 million. Cells marked n/a denote strata with insufficient liquidations to obtain estimates.

	All Funds		Large Funds		Small Funds		Log Rank	All Funds		Large Funds		Small Funds		Log Rank
	Median	S.E.	Median	S.E.	Median	S.E.	p-Value	Median	S.E.	Median	S.E.	Median	S.E.	p-Value
	Panel A: All 2446 Funds							**Panel B: 1413 Funds Above $5 million**						
All exits														
Systematic	53	1.74	129	5.65	45	1.53	<0.001	73	2.75	133	11.80	65	2.42	<0.001
Discretionary	44	2.05	82	8.98	39	2.04	<0.001	57	3.31	96	17.33	54	2.72	0.0009
Options	47	3.97	150	14.24	44	4.54	0.0017	71	5.96	66	2.66	72	5.41	0.7596
All funds	50	1.30	110	8.22	43	1.06	<0.001	68	1.99	129	6.06	61	1.98	<0.001
Liquidated														
Systematic	60	1.91	144	18.89	51	1.8	<0.001	82	3.83	221	n/a	72	2.7	<0.001
Discretionary	51	2.15	108	10.85	47	2.12	<0.001	69	3.74	132	40.43	61	3.89	0.0002
Options	53	5.1	150	14.24	50	4.11	0.0143	78	16.7	66	2.66	78	18.63	0.7749
All funds	57	1.52	131	9.23	49	1.31	<0.001	77	2.77	165	18.41	70	2.07	<0.001
Failed only														
Systematic	73	2.71	221	n/a	60	2.24	<0.001	114	8.6	n/a	n/a	92	5.86	<0.001
Discretionary	61	3.52	163	16.74	55	2.76	<0.001	82	7.58	163	8.8	76	8.09	0.0042
Options	69	12.09	n/a	n/a	67	10.4	0.0602	n/a	n/a	n/a	n/a	n/a	n/a	n/a
All funds	69	2.26	209	20.49	59	1.77	<0.001	107	5.54	n/a	n/a	89	4.67	<0.001
Panel C:	**Median Survival for other types of exits**													
Merged funds	52	9.63						53	9.92					
Not Reporting funds	36	5.74						45	3.74					
Fraud	28	4.19						23	4.22					
Self-selected funds	36	1.30						36	3.32					

Table 1.7: **Kaplan-Meier Estimated Median Survival Times (Half-Life) by Strategy and Exit Type for 892 Funds Filtered by Dynamic AUM**

Table 1.7 reports Kaplan-Meier median survival time in months along with the standard error (S.E.) for 892 funds selected with a dynamic AUM filter. Large and small funds are those CTAs that had mean assets for the period January 1994 to December 2009 that were above or below the mean assets of all funds in the same strategy. The Log-Rank p-value is for the Log-Rank test for equality of the survival functions of the large funds and small funds groups. In Panel A survival time is defined as time until exit into the graveyard whilst Panel B shows the survival times for the funds filtered for failure. Cells marked n/a denote strata with insufficient liquidations to obtain estimates. Counter Trend and Vol. Arb. are not included due to insufficient data.

Panel A: All Exits	All Funds		Large Funds		Small Funds		Log Rank
	Median	S.E.	Median	S.E.	Median	S.E.	p-Value
Options	98	19.19	66	4.9	98	13.21	0.7633
Short-Term Trend	97	9.39	204	30.72	68	8.51	<0.0001
Medium-Term Trend	92	6.01	n/a	n/a	83	5.67	<0.0001
Long-Term Trend	90	12.63	165	9.86	77	10.6	0.0719
Pattern Recognition	89	16.11	n/a	n/a	84	15.87	0.1457
Fundamental	75	4.00	162	45.24	71	5.83	0.0752
Discretionary Spread/RV	67	11.19	83	13.15	52	10.01	0.7817
Systematic Spread/RV	63	10.43	106	18.06	60	3.07	0.0336
Fundamental and Technical	62	4.97	98	6.56	59	4.83	0.201
Technical	57	4.04	52	12.25	58	6.36	0.9045
Systematic	105	19.56	204	22.78	77	3.09	<0.0001
Discretionary	65	4.00	98	15.26	60	3.93	0.0238
Options	98	19.19	66	4.90	98	13.21	0.7633
All Funds	**77**	**2.89**	**162**	**16.78**	**71**	**2.40**	**<0.0001**

Panel B: Failed Funds	All Funds		Large Funds		Small Funds		Log Rank
	Median	S.E.	Median	S.E.	Median	S.E.	p-Value
Short-Term Trend	152	16.98	160	20.5	128	16.07	<0.0001
Medium-Term Trend	145	11.18	n/a	n/a	119	11.16	<0.0001
Long-Term Trend	141	12.57	n/a	n/a	124	21.38	0.0307
Pattern Recognition	127	15.38	n/a	n/a	109	14.51	0.1056
Discretionary Spread/RV	125	2.93	n/a	n/a	125	2.94	0.6224
Systematic Spread/RV	106	18.58	130	24.73	76	16.24	0.1038
Options	105	n/a	n/a	n/a	105	n/a	n/a
Technical	97	16.56	52	n/a	97	16.65	0.9698
Fundamental and Technical	96	34.39	176	6.73	81	23.37	0.4396
Fundamental	93	28.99	162	14.76	77	11.44	0.2979
Systematic	144	8.44	172	9.61	114	8.79	<0.0001
Discretionary	100	11.14	163	6.01	93	12.57	0.0714
Options	105	10.11	98	11.2	105	9.58	0.5873
All Funds	**130**	**7.67**	**136**	**8.78**	**109**	**6.30**	**<0.0001**

Table 1.8: **Log Rank Test for CTAs Above and Below the Median for 892 funds filtered by dynamic AUM**

Table 1.8 reports median values of the covariates together with median survival times for funds above and below median covariate values for the period January 1994 to December 2009. The Log-Rank p-value is for the Log-Rank test for equality of the survival functions of the two groups.

		50% Survival in Years			
Variable	Median Value	Above	Below	Chi-Square	p-Value
Mean Monthly Return	0.95%	14.67	8.25	37.87	<0.0001
Average Millions Managed	$103.00	12.17	9.08	48.25	<0.0001
Standard Deviation	4.53%	10.33	12.00	0.64	0.4227
Performance Fees	20.06%	13.42	10.42	3.21	0.0732
Management Fees	2.00%	10.83	6.42	0.1	0.7535
Minimum Purchase	$1,922,391	12.08	10.75	2.91	0.088

Table 1.9: **Hazard ratios for the GHPR (2005) Cox PH Model for Attrition**

Table 1.9 reports results for the Gregoriou, Hubner, Papageorgiou and Rouah (2005) Cox proportional hazards model for the period January 1994 to December 2009. Included are the coefficient estimates, β, hazard ratios, confidence intervals, Chi-square and corresponding p-values for the two-tailed test of a regression coefficient equal to zero. Also included are the Likelihood ratio test and the Wald test, both measuring the goodness of fit of the model.

Variable	Coefficient	Hazard Ratio	Confidence Intervals	Chi-square	p-Value
Mean monthly return	-0.177	0.838	(.709, .990)	-2.07	0.038
Average millions	-0.003	0.997	(.996, .998)	-5.77	<0.0001
Standard deviation	0.001	1.001	(.999, 1.001)	-0.43	0.669
Incentive fees	-0.016	0.984	(.959, 1.010)	-1.22	0.222
Management fees	0.142	1.152	(1.052, 1.263)	3.04	0.002
Minimum purchase	-0.001	0.999	(.996, 1.001)	-0.98	0.328
Likelihood ratio test (χ^2_1)	91.53***				
Global Wald test	55.22***				

Table 1.10: **Hazard ratios for the Liang and Park (2010) Cox PH Model for Attrition**

Table 1.10 reports coefficient estimates, β and hazard ratios from the Cox (1972) PH model for the period January 1994 to December 2009. The table includes models with fixed and time varying covariates. Failure is defined as exit to the graveyard. ***, **, and * denote that the coefficient estimate and the hazard ratios are statistically significant at the 1%, 5% and 10% levels, respectively. Also included are tests measuring the goodness of fit of the model. The Global Ph test is a Wald test that tests if all the variables jointly satisfy the proportional hazard assumption. Rho is a slope coefficient estimate of Schoenfeld residuals of each variable against time and tests if each variable satisfies the proportional hazard assumption.

Classification	Total	Event (Exit)	Censored	Percent Censored
All Exits	817	529	288	35.3

Variable	Hazard Ratio	Rho	Hazard Ratio	Rho	Hazard Ratio	Rho	Hazard Ratio	Rho	Hazard Ratio	Rho
MODEL	**STD**		**SEM**		**VAR**		**ES**		**TR**	
Panel A:										
Univariate Model										
Risk measure	0.97**	0.01	1.00	0.02	0.99	-0.01	0.94***	0.01	0.98	0.03
Likelihood ratio test (χ^2_1)	6.40**		0.01		1.51		26.98***		1.95	
Panel B:										
Multivariate Model										
Risk measure	0.98	0.00	1.00	0.03	0.99*	0.00	0.93***	-0.01	0.97	0.04
Mean return 1 yr	0.90	0.02	1.02	-0.04	1.02	-0.04	1.02	-0.05	1.03	-0.05
Mean AUM 1yr	1.00	-0.01	1.00	-0.01	1.00	-0.01	1.00	-0.01	1.00	-0.01
St. Dev. AUM	1.00**	0.11***	1.00**	0.11***	1.00**	0.11***	1.00**	0.11***	1.00**	0.11***
Leverage	0.41***	0.00	0.40***	0.00	0.39***	0.00	0.39***	0.00	0.40***	0.00
HWM	1.59**	-0.01	1.70	0.00	1.66**	-0.01	1.74***	-0.01	1.65**	-0.01
D1 (Discretionary)	1.37***	-0.02	1.37***	-0.01	1.35***	-0.02	1.39***	-0.02	1.34***	-0.02
D2 (Options)	0.82	-0.01	0.74	0.00	0.75	0.00	0.57	0.00	0.81	0.01
Likelihood ratio test (χ^2_1)	119.73***		109.77***		114.03***		140.08***		112.24***	
Global Ph Wald test	39.54***		40.46***		40.75***		40.46		41.88***	

Table 1.11: **Hazard ratios for the Liang and Park (2010) Cox PH Model for Liquidation**

Table 1.11 reports coefficient estimates, β and hazard ratios from the Cox (1972) PH model for the period January 1994 to December 2009. The table includes models with fixed and time varying covariates. Failure is defined based on the performance and size criteria defined previously. ***, **, and * denote that the coefficient estimate and the hazard ratios are statistically significant at the 1%, 5% and 10% levels, respectively. Also included are tests measuring the goodness of fit of the model. The Global Ph test is a Wald test that tests if all the variables jointly satisfy the proportional hazard assumption. Rho is a slope coefficient estimate of Schoenfeld residuals of each variable against time and tests if each variable satisfies the proportional hazard assumption.

Classification	Total	Event (Exit)	Censored	Percent Censored						
All Exits	817	441	376	46.0						
Variable	Hazard Ratio	Rho	Hazard Ratio	Rho	Hazard Ratio	Rho	Hazard Ratio	Rho	Hazard Ratio	Rho
MODEL	**STD**		**SEM**		**VAR**		**ES**		**TR**	
Panel A: Univariate Model										
Risk measure	0.96**	0.02	1.00	0.03	0.99	-0.01	0.93***	0.02	0.98	0.05
Likelihood ratio test (χ^2_1)	5.58**		0.03		0.83		28.79***		1.46	
Panel B: Multivariate Model										
Risk measure	0.98	-0.04	1.00	0.03	0.98**	-0.01	0.93***	0.01	0.97*	0.04
Mean return 1 yr	0.74***	0.08***	0.95	-0.02	0.95*	-0.02	0.96	-0.03	0.95	-0.02
Mean AUM 1yr	1.00***	-0.14***	1.00***	-0.13***	1.00***	-0.13***	1.00***	-0.13***	1.00***	-0.13***
St. Dev. AUM	1.00**	0.15***	1.00**	0.15***	1.00**	0.15***	1.00**	0.15***	1.00**	0.15***
Leverage	0.20***	0.00	0.20***	0.00	0.20***	0.00	0.20***	0.00	0.20***	0.00
HWM	1.45	-0.01	1.61*	-0.01	1.55*	-0.02	1.65*	-0.01	1.53*	-0.01
D1 (Discretionary)	1.31***	-0.03	1.30**	-0.01	1.29**	-0.02	1.33***	-0.02	1.28**	-0.02
D2 (Options)	0.86	-0.01	0.77	-0.01	0.78	-0.01	0.61	-0.01	0.85	0.01
Likelihood ratio test (χ^2_1)	180.96***		160.52***		166.03***		190.84***		163.55***	
Global Ph Wald test	25.82***		18.51**		18.56**		18.18**		19.61***	

Table 1.12: **A Survival Analysis to Predict Failure of CTAs, Fixed Covariates - Base Model**

Table 1.12 reports coefficient estimates, β and hazard ratios from the Cox (1972) PH model for the period January 1994 to December 2009. The table includes fixed covariates only. Failure is defined based on the performance and size criteria defined previously. ***, **, and * denote that the coefficient estimate and the hazard ratios are statistically significant at the 1%, 5% and 10% levels, respectively. Also included are tests measuring the goodness of fit of the model. The Global Ph test is a Wald test that tests if all the variables jointly satisfy the proportional hazard assumption. Rho is a slope coefficient estimate of Schoenfeld residuals of each variable against time and tests if each variable satisfies the proportional hazard assumption.

Variable	Coefficient	Hazard Ratio	Rho	Coefficient	Hazard Ratio	Rho	Coefficient	Hazard Ratio	Rho	Coefficient	Hazard Ratio	Rho
Model	Specification (i)			Specification (ii)			Specification (iii)			Specification (iv)		
Mean return	-0.93	0.40***	0.07	-0.71	0.49***	0.03	-0.96	0.38***	0.13***	-0.92	0.40**	0.15**
Standard deviation	0.07	1.07***	0.12*	0.06	1.06***	0.08	0.24	1.27***	-0.26***	-0.01	0.99	0.06
Skewness				-0.15	0.86**	0.04	-0.34	0.71***	0.12**			
Kurtosis				-0.03	0.98*	0.03	0.00	1.00	-0.05	-0.04	0.96***	0.02
Winning ratio				-1.12	0.33**	-0.03	-2.50	0.08***	0.04	-2.56	0.08***	-0.02
Max drawdown							0.05	1.05***	-0.29***			
D1 (drawdown/STD >1)										-0.28	0.75*	-0.07
D2 (drawdown/STD >2)										0.12	1.12	0.06
D3 (drawdown/STD >3)										1.14	3.13***	0.04
Mean AUM	-0.01	0.99***	0.01	-0.01	1.00	-0.18***	0.00	1.00	-0.15**	0.00	1.00*	-0.18***
Std. AUM				-0.01	0.99***	0.19***	-0.01	0.99***	0.17***	-0.01	0.99***	0.20***
Management fee	0.12	1.13**	0.09	0.12	1.09**	-0.06	0.13	1.14**	-0.10*	0.12	1.13**	-0.05
Incentive fee	-0.02	0.98	-0.05	-0.02	0.98	0.00	-0.40	0.96**	0.03	-0.02	0.98	0.02
Hurdle				-47.05	0.00	0.00		0.00				
Leverage				-1.65	0.19***	-0.02	-1.60	0.20***	-0.01	-1.59	0.20***	-0.03
HWM				0.35	1.42	0.02	0.41	1.50	0.01	0.57	1.76*	-0.02
Min. investment	0.00	1.00	-0.04	0.00	1.00	-0.03	0.00	1.00	-0.01	0.00	1.00	-0.04
D1 (Discretionary)				0.45	1.57***	0.00	0.44	1.55***	0.02	-0.41	1.51***	-0.03
D2 (Options)				0.63	1.89	-0.02	0.33	1.39	0.01	0.96	2.61**	-0.04
Likelihood ratio (χ^2_1)	153.09***			222.41***			226.65***			152.25***		
Global Ph Wald test	10.05			26.82			58.92***			32.44		

Table 1.13: **A Comparison of the Effect of Risk Measures on Survival of CTAs**

Table 1.13 reports coefficient estimates, β and hazard ratios from the Cox (1972) PH model for the period January 1994 to December 2009. The table includes models with fixed and time varying covariates. Failure is defined based on the performance and size criteria defined previously. ***, **, and * denote that the coefficient estimate and the hazard ratios are statistically significant at the 1%, 5% and 10% levels, respectively. Also included are tests measuring the goodness of fit of the model. The Global Ph test is a Wald test that tests if all the variables jointly satisfy the proportional hazard assumption. Rho is a slope coefficient estimate of Schoenfeld residuals of each variable against time and tests if each variable satisfies the proportional hazard assumption.

Classification	Total	Event (Exit)	Censored	Percent Censored						
All Exits	817	301	516	63.2						
Variable	Hazard Ratio	Rho	Hazard Ratio	Rho	Hazard Ratio	Rho	Hazard Ratio	Rho	Hazard Ratio	Rho
MODEL	**STD**		**SEM**		**VAR**		**ES**		**TR**	
Panel A:										
Univariate Model										
Risk measure	1.01	0.09	1.07***	0.10*	1.00	0.07	0.93***	0.00	1.02**	0.17
Likelihood ratio test (χ^2_1)	0.03		7.53**		0.62		32.98***		1.14	
Panel B:										
Multivariate Model										
Risk measure	0.98	0.06	1.05**	0.08	1.00	0.02	0.93***	-0.02	1.02**	0.13**
Mean return 1 yr	0.84***	-0.07	0.85***	-0.05	0.84***	-0.07	0.85***	-0.08	0.84***	-0.06
Mean AUM 1yr	1.00***	-0.12***	1.00***	-0.12**	1.00***	-0.12**	1.0***	-0.12**	1.00***	-0.11
St. Dev. AUM	1.00	0.14***	1.00	0.14***	1.00	0.14***	1.0	0.14***	1.00	0.14***
Leverage	0.22**	-0.02	0.21***	-0.02	0.22**	-0.02	0.22***	-0.02	0.22**	-0.02
HWM	1.73*	-0.02	1.85**	-0.02	1.75*	-0.03	1.80 **	-0.03	1.76*	-0.02
D1 (Discretionary)	1.41***	0.01	1.43***	0.02	1.42***	0.01	1.46***	0.01	1.44***	0.02
D2 (Options)	1.07	-0.02	1.03	-0.03	1.07	-0.02	0.83	-0.04	1.10	-0.02
Likelihood ratio test (χ^2_1)	149.45***		152.06***		148.74***		180.49***		147.16***	
Global Ph Wald test	15.80		15.78		14.59		14.32*		18.00**	

Table 1.14: **A Comparison of the Effect of Risk Measures on Survival of CTAs**

Table 1.14 reports coefficient estimates, β and hazard ratios from the Cox (1972) PH model for the period January 1994 to December 2009. The table includes models with fixed and time varying covariates. Failure is defined based on the performance and size criteria defined previously. ***, **, and * denote that the coefficient estimate and the hazard ratios are statistically significant at the 1%, 5% and 10% levels, respectively. Also included are tests measuring the goodness of fit of the model. The Global Ph test is a Wald test that tests if all the variables jointly satisfy the proportional hazard assumption. Rho is a slope coefficient estimate of Schoenfeld residuals of each variable against time and tests if each variable satisfies the proportional hazard assumption.

Variable	Hazard Ratio	Rho	Hazard Ratio	Rho	Hazard Ratio	Rho	Hazard Ratio	Rho	Hazard Ratio	Rho	Hazard Ratio	Rho
Multivariate Model	**STD**		**SEM**		**VAR**		**ES**		**TR**		**Drawdown/ STD**	
Risk measure	1.02	-0.04	1.09***	0.03	1.01	-0.09	0.90***	-0.04	1.04**	0.02		
D1 (drawdown/STD >1)											0.63***	-0.05
D2 (drawdown/STD >2)											0.59**	0.09
D3 (drawdown/STD >3)											1.13**	0.03
Mean return	0.57***	0.11***	0.52***	0.09*	0.57***	0.13***	0.57***	0.09**	0.53***	0.09**	0.52***	0.15***
Skewness	0.87*	0.04	0.93	0.07	0.86**	0.05	0.97	0.07	0.93	0.06	0.92	0.05
Kurtosis	0.98	0.05	0.98	0.04	0.98	0.05	0.96**	0.06	0.97*	0.07	0.97*	0.01
Winning ratio	0.35	-0.04	0.61	-0.01	0.38	-0.05	0.46	-0.02	0.57	-0.02	0.29	-0.05
Log AUM	0.85***	-0.22***	0.86***	-0.21***	0.85***	-0.24***	0.84***	-0.22***	0.85***	-0.22***	0.84***	-0.20***
St. Dev. AUM	1.00***	0.17***	1.00***	0.17***	1.00***	0.17***	1.00***	0.17***	1.00***	0.17***	1.00***	0.17***
Management fee	1.14**	-0.02	1.11*	-0.03	1.14**	-0.01	1.14**	-0.04	1.13**	-0.03	1.17***	-0.05
Incentive fee	0.98	-0.02	0.98	-0.01	0.98	-0.02	0.98	-0.03	0.98	-0.01	0.98	-0.02
Leverage	0.21***	-0.01	0.20***	-0.01	0.21***	-0.01	0.21***	-0.01	0.21***	-0.01	0.22**	-0.01
HWM	1.76*	0.04	1.75*	0.05	1.75*	0.05	1.82**	0.04	1.78*	0.05	1.92**	-0.01
Min. investment	1.00	0.02	1.00	0.02	1.00	0.02	1.00	0.02	1.00	0.02	1.00	0.01
D1 (Discretionary)	1.54***	0.03	1.50***	0.02	1.53***	0.03	1.53***	0.02	1.54***	0.01	1.40**	0.02
D2 (Options)	1.35	-0.01	1.32	-0.01	1.36	-0.01	1.15	-0.04	1.60	-0.02	1.96*	-0.02
Likelihood ratio test (χ^2_1)	199.02***		208.43***		199.70***		228.70***		202.16***		203.45***	
Global Ph Wald test	32.34***		30.97***		34.42***		32.34***		32.49***		38.77***	

Table 1.15: **A Comparison of the Effect of Risk Measures on Survival of CTAs with Time-Varying AUM and Flow**

Table 1.15 reports coefficient estimates, β and hazard ratios from the Cox (1972) PH model for the period January 1994 to December 2009. The table includes models with fixed and time varying covariates. Failure is defined based on the performance and size criteria defined previously. ***, **, and * denote that the coefficient estimate and the hazard ratios are statistically significant at the 1%, 5% and 10% levels, respectively. Also included are tests measuring the goodness of fit of the model. The Global Ph test is a Wald test that tests if all the variables jointly satisfy the proportional hazard assumption. Rho is a slope coefficient estimate of Schoenfeld residuals of each variable against time and tests if each variable satisfies the proportional hazard assumption.

Variable	Hazard Ratio	Rho	Hazard Ratio	Rho	Hazard Ratio	Rho	Hazard Ratio	Rho	Hazard Ratio	Rho	Hazard Ratio	Rho
Multivariate Model	**STD**		**SEM**		**VAR**		**ES**		**TR**		**Drawdown/ STD**	
Risk measure	1.02	-0.02	1.10***	0.04	1.01*	-0.07	0.90***	-0.03	1.05**	0.03		
D1 (drawdown/STD >1)											0.59***	-0.05
D2 (drawdown/STD >2)											1.01**	0.09
D3 (drawdown/STD >3)											1.71	0.06
Mean return	0.52***	0.09**	0.48***	0.06	0.52***	0.04	0.53***	0.08*	0.49***	0.07	0.87***	-0.08
Skewness	0.85**	0.02	0.91	0.06	0.84**	0.03	0.93	0.04	0.91	0.04	0.75***	0.13***
Kurtosis	0.98	0.05	0.97*	0.04	0.98	0.06	0.96**	0.05	0.97**	0.07	0.97**	0.00
Winning Ratio	0.22*	-0.06	0.39	-0.04	0.25	-0.07	0.23*	-0.05	0.35	-0.03	0.05***	0.05
AUM(t)	0.99***	0.02	0.99***	0.02	0.99***	0.02	0.99***	0.02	0.99***	0.02	0.99***	0.02
Flow(t)	0.12***	-0.09	0.12***	-0.09	0.12***	-0.09	0.12***	-0.08	0.12***	-0.09	0.12***	-0.06
Management fee	1.13**	-0.04	1.10	-0.05	1.13**	-0.03	1.13**	-0.06	1.11*	-0.04	1.09	-0.02
Incentive fee	0.98	0.00	0.98	0.02	0.98	0.00	0.98	-0.02	0.98	0.01	0.96**	-0.02
Leverage	0.22**	-0.02	0.22***	-0.02	0.22***	-0.02	0.23**	-0.02	0.22***	-0.02	0.24**	-0.01
HWM	1.31	0.03	1.32	0.04	1.31	0.03	1.34	0.03	1.34	0.03	1.48	0.00
Min. investment	1.00	-0.01	1.00	-0.01	1.00	-0.01	1.00	-0.01	1.00	-0.01	1.00	0.00
D1 (Discretionary)	1.55***	0.01	1.52***	0.00	1.54***	0.01	1.54***	0.01	1.55***	-0.01	1.61***	-0.03
D2 (Options)	1.48	-0.01	1.40	-0.01	1.49	-0.01	1.15	-0.03	1.73	-0.01	1.95*	0.02
Likelihood ratio test (χ^2_1)	289.10***		299.79***		290.28***		316.70***		292.92***		288.47***	
Global Ph Wald test	12.78		13.08		13.84		13.62		13.75		20.38	

Table 1.16: **Survival Analysis for All Strategies**

Table 1.16 reports coefficient estimates, β and hazard ratios from the Cox (1972) PH model for the period January 1994 to December 2009. The table includes models with fixed and time varying covariates and includes 12 strategies. Failure is defined based on the performance and size criteria defined previously. ***, **, and * denote that the coefficient estimate and the hazard ratios are statistically significant at the 1%, 5% and 10% levels, respectively. Also included are tests measuring the goodness of fit of the model. The Global Ph test is a Wald test that tests if all the variables jointly satisfy the proportional hazard assumption. Rho is a slope coefficient estimate of Schoenfeld residuals of each variable against time and tests if each variable satisfies the proportional hazard assumption.

Variable	Hazard Ratio	Rho	Hazard Ratio	Rho	Hazard Ratio	Rho
Model	**STD**		**TR**		**Drawdown/ STD**	
Risk measure	1.03	-0.05	1.06***	-0.01		
D1 (drawdown/STD >1)					0.51***	-0.06
D2 (drawdown/STD >2)					1.01**	0.10*
D3 (drawdown/STD >3)					1.00*	0.05
Mean return	0.50***	0.10**	0.46***	0.07*	0.52***	0.12***
Skewness	0.84**	0.01	0.90	0.03	0.76***	0.05
Kurtosis	0.98	0.07	0.97**	0.08	0.98	0.02
Winning ratio	0.20*	-0.06	0.31	-0.04	0.05***	-0.03
AUM(t)	0.99***	0.01	0.99***	0.02	0.99***	0.03
Flow(t)	0.12***	-0.08*	0.12***	-0.08	0.12***	-0.08
Management fee	1.16**	-0.02	1.14**	-0.03	1.17***	-0.03
Incentive fee	0.99	0.01	0.99	0.02	1.00	0.01
Leverage	0.22**	-0.03	0.23**	-0.03	0.22**	-0.03
HWM	1.15	0.02	1.19	0.02	1.08	0.01
Min. investment	1.00	-0.01	1.00	-0.01	1.00	0.01
D1 (Fundamental)	0.65	0.11**	0.62*	0.11*	0.62*	0.07
D2 (Technical)	0.94	0.03	0.94	0.04	0.84	0.01
D3 (Disc Spread/RV)	0.80	0.08	0.84	0.08	0.86	0.04
D4 (Options)	0.84	0.02	0.95	0.02	0.85	0.02
D5 (Pattern Rec.)	0.66	0.06	0.66	0.06	0.59	0.06
D6 (Counter Trend)	2.50*	0.04	2.50*	0.05	2.40	0.04
D7 (Systematic Spread/RV)	1.03	0.09	0.99	0.10*	1.00	0.08
D8 (Short-term)	0.41***	-0.06	0.42***	-0.05	0.41***	-0.07
D9 (Medium-term)	0.48***	0.07	0.48***	0.08	0.48***	0.05
D10 (Long-term)	0.67*	0.07	0.65	0.07	0.68	0.07
Likelihood ratio test (χ_1^2)	308.74***		311.86***		323.37	
Global Ph Wald test	26.39		26.49		37.78	

Figure 1.1: **Assets Under Management for CTA Industry, 1994-2009.**

Figure 1.1 shows the growth of the assets under management for the entire CTA industry starting from January 1994 and ending in December 2009. Included are the onshore and offshore vehicles of the funds and various share classes.

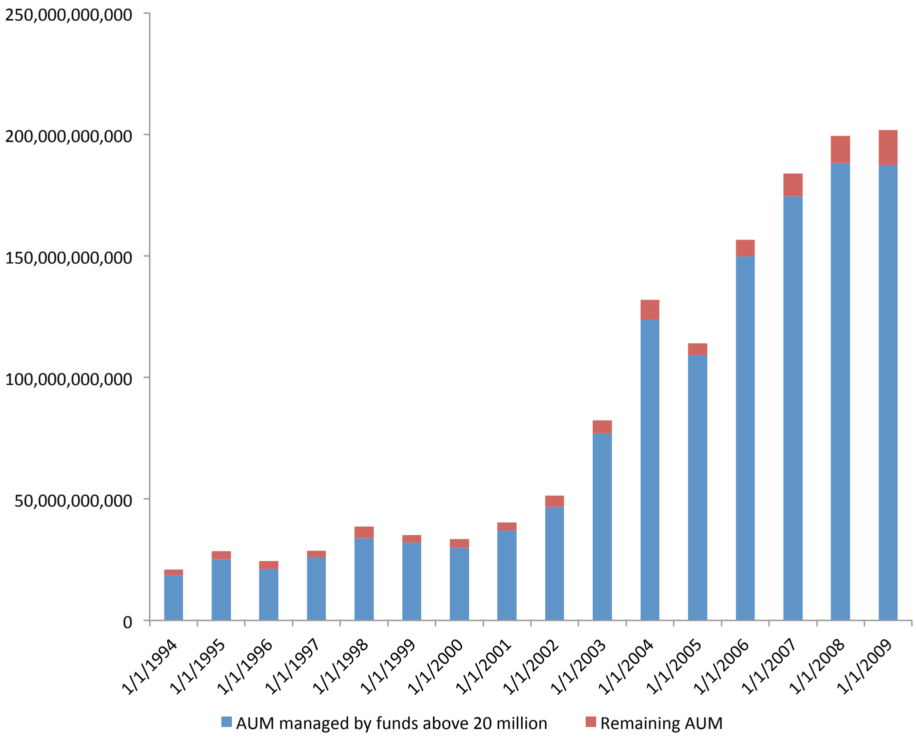


Figure 1.2: **Failed Fund with Small AUM**

Figure 1.2 shows VAMI and AUM for a fund that failed in terms of downside risk measures and had negative return in the last six months yet its assets remained stable. Such a fund would not be caught by Liang and Park's (2010) filter. Source: PerTrac Analytical Platform.

Figure 1.3: **Fund With Lost Assets More Than 12 Months Before End of Data**

Figure 1.3 shows VAMI and AUM for a fund whose assets dropped prior to 12 months before the end of data. Such a fund would not be caught by Liang and Park's (2010) filter. Source: PerTrac Analytical Platform.

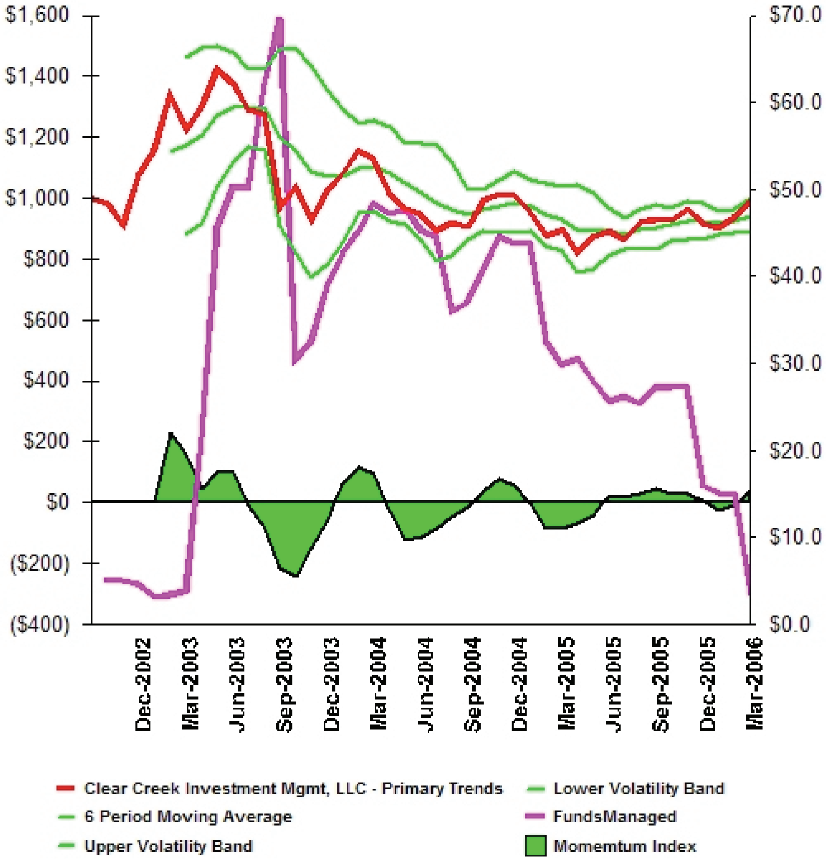


Figure 1.4: **Fund With Positive Average Return in the Last Six Months**

Figure 1.4 shows VAMI and AUM for a fund which experienced a large drawdown of 78.24% and a loss of assets yet in the last six months prior to termination its average return was positive. Such a fund would not be caught by Liang and Park's (2010) filter. Source: PerTrac Analytical Platform.

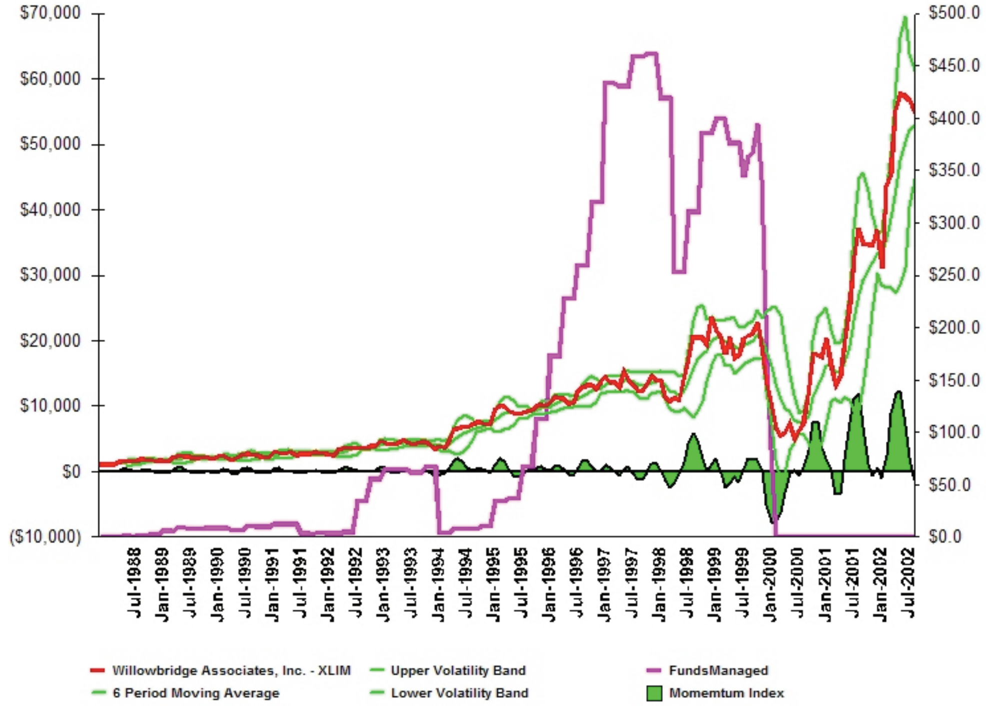
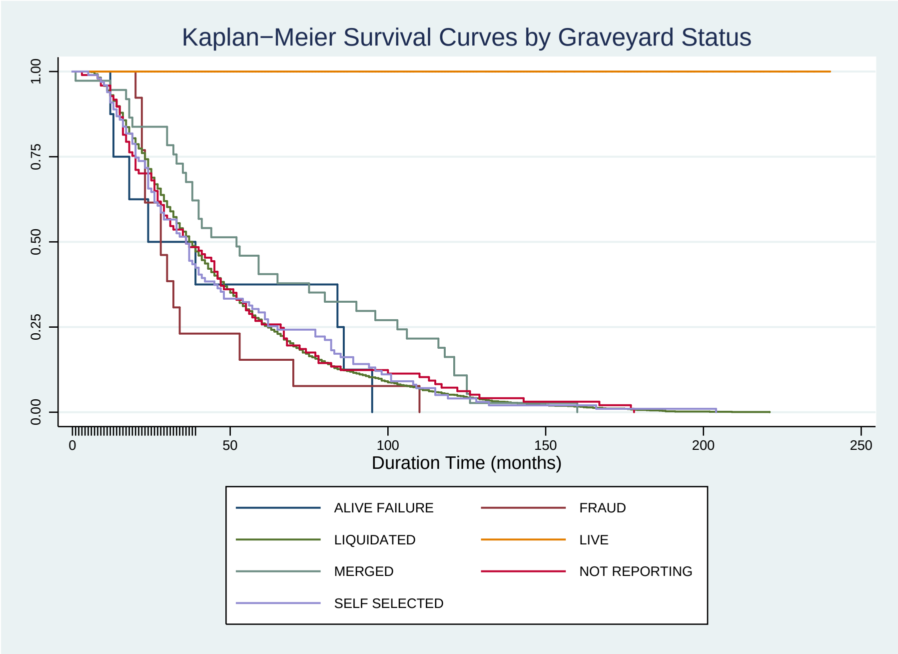


Figure 1.5: **Non-Parametric Survival and Hazard Curves**

Figure 1.5 shows survival and hazard curves for all 2446 funds in the sample by exit status.



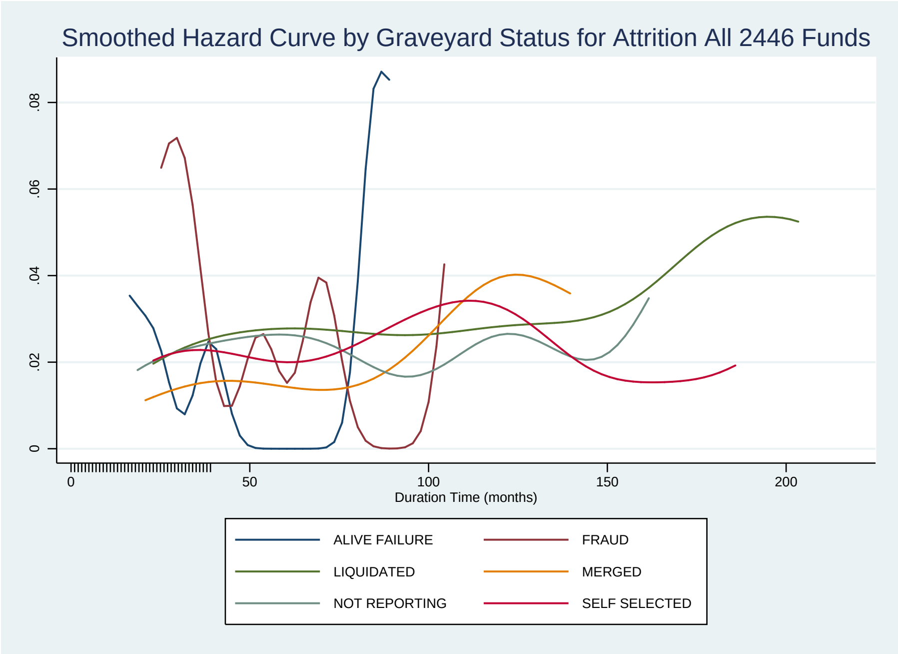
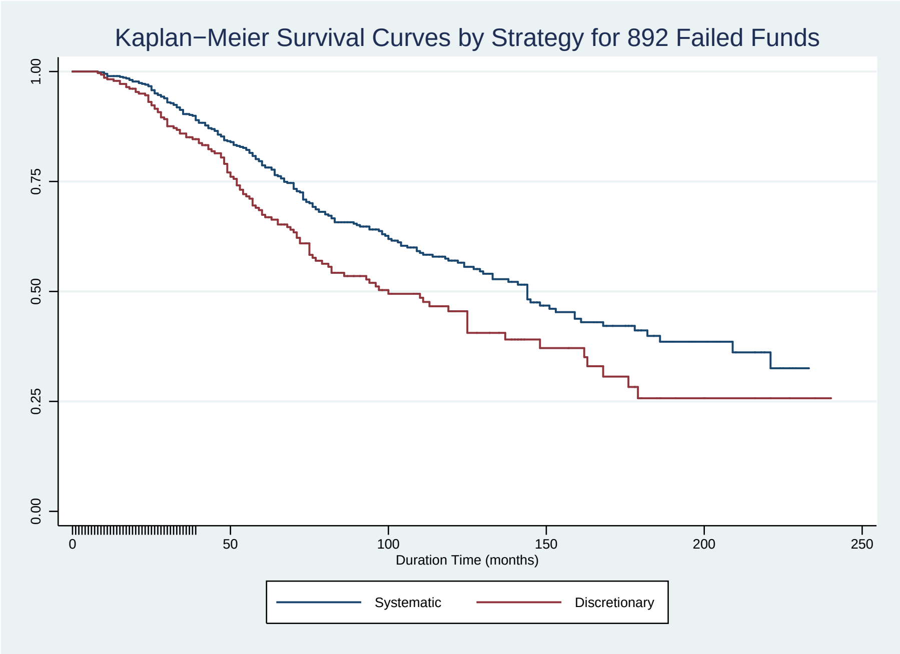


Figure 1.6: **Non-Parametric Survival and Hazard Curves**

Figure 1.6 shows survival and hazard curves for 892 funds filtered by dynamic AUM. The graphs show survival and hazard curves of systematic and discretionary for failed funds.



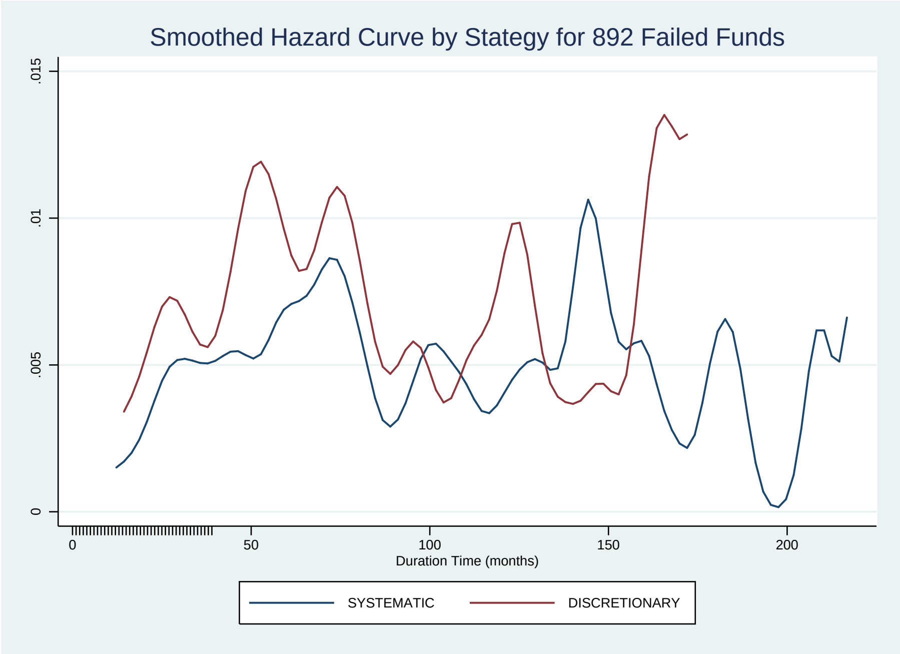
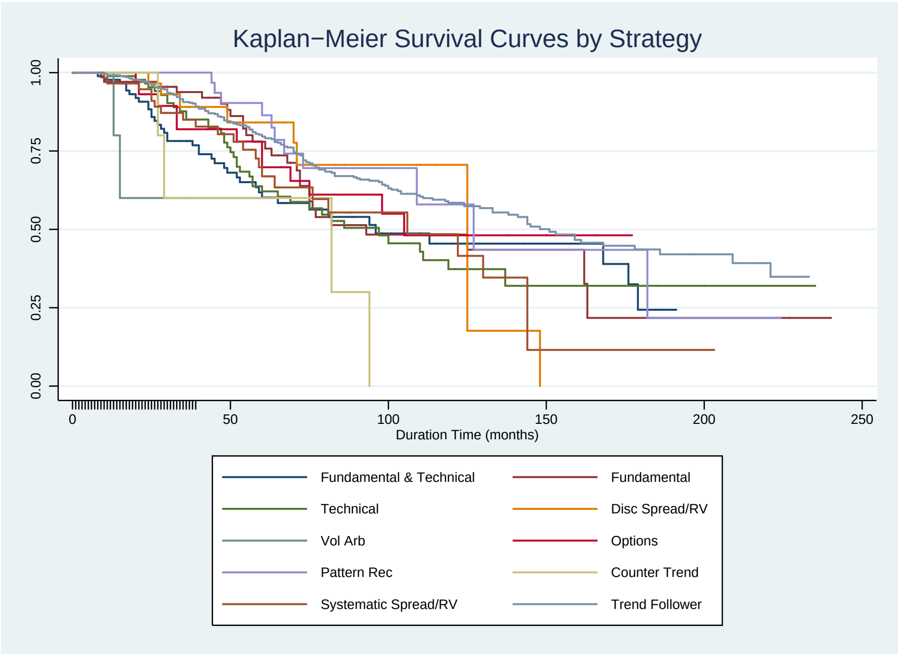
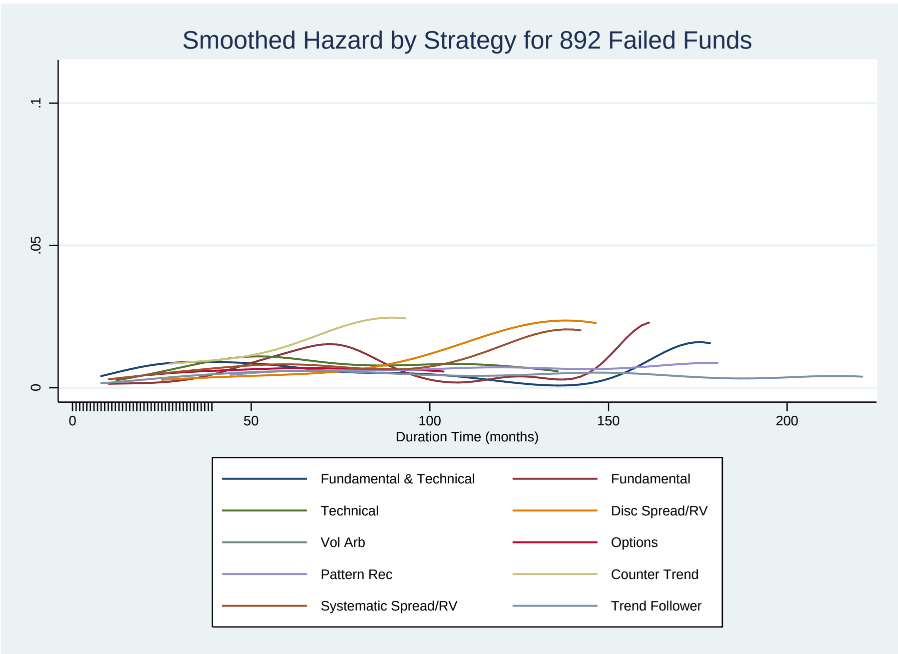


Figure 1.7: **Non-Parametric Survival and Hazard Curves**

Figure 1.7 shows survival and hazard curves for 892 funds filtered by dynamic AUM. The graphs show survival and hazard curves for failed funds across sub-strategies.





Chapter 2

Performance and Persistence of Commodity Trading Advisors

2.1 Introduction

In the last few years we have witnessed a major downturn in the world economy and financial markets. Many institutional investors have been hit by significant losses from their investments across multiple asset classes including hedge funds. Whilst the hedge fund industry had been growing at an impressive rate over the last decade, the financial crisis led to a significant outflow of assets following disappointing returns. The financial crisis is clearly not over with economies plunging into deep recessions across many parts of the world. In such an uncertain economic environment institutional and private investors are faced with difficult asset allocation decisions since even hedge funds which until recently were considered to be market neutral have been hit with significant losses. With rising total debt levels across major economies such as the US, UK and EU, the risks of deflation or hyperinflation are high. There is however an asset class that is better suited to such an environment. Faced with such uncertainty investors may benefit from investing in the most liquid of instruments such as futures.

Managed futures are also commonly referred to as CTAs and are a particular subset of the hedge fund universe with many regulatory features and characteristics similar to that of hedge funds. Hedge funds and CTAs have been attracting increased interest from academics and investors. Baquero et al. (2005) document that long/short equity and managed futures were the most popular investment styles among hedge funds during 1990-2000 period. Although the number and assets under management of CTAs have seen a dramatic growth in the past 20 years, there is little consensus in the empirical literature on the performance and persistence of managed futures. The earliest studies of Elton, Gruber and Rentzler (1987, 1989 and 1990) on Commodity Pool Operators have concluded that publicly traded commodity pools are unable to generate any superior performance and most of the performance is retained by the managers through fees.[1] A recent study by Bhardwaj et al. (2008) mirrors the findings of Elton et al. (1990) and concludes that net of fees returns of CTAs fail to significantly exceed those of T-bills. Other authors, however, have argued that CTAs do outperform the market and that numerous CTAs show persistence over a horizon of at least three months, Gregoriou et al. (2010) and Capocci (2005). Edwards and Caglayan (2001), Liang (2003) and Schneeweis and Georgiev (2002) have further demonstrated that unlike hedge funds, CTAs offer significant protection in down markets and have higher returns with an inverse correlation to equity markets during downturns. Consequently, they conclude that institutional investors should use CTAs as a hedging instrument in their portfolio construction.

These recent findings raise some interesting questions. In light of the negative publicity of CTAs offered by Elton et al. (1990), what is the average performance of CTAs and does an average CTA have any ability to deliver alpha? If not, are there any CTAs in the cross section that are capable of delivering alpha and if so does that performance persist? What are the factors that are driving this performance and persistence?

To answer these questions, this study employs data on a large-cross section of CTAs with a novel strategy classification to shed light on the performance and persistence of

[1] Commodity Pool Operators are entities that accept funds for the purpose of trading commodity futures contracts. A CPO can make its own trading decisions but will frequently contract CTAs. Both CPOs and CTAs are regulated by the US federal government through the CFTC and an oversight from NFA. (From http://richard-wilson.blogspot.com/2009/07/what-is-commodity-pool-operator.html).

CTA managers between 1990 and 2010. This twenty year period is the longest studied in the CTA literature and spans both bull (pre 2000 and 2007) and bear markets, including several financial crises: the Russian default crises of 1998, the burst of the tech bubble in Spring 2000 as well as the credit crisis of 2008-2009. In this study CTAs are classified according to two major style groups: systematic or discretionary. Anecdotal evidence suggests that this is indeed the industry practice within most CTAs. A recent article in the Financial Times discusses the benefits of the two strategies[2]. Previous studies, Billigsley and Chance (1996), Brown et al. (2001), Diz (1999), etc., have all studied CTAs as a single group. In contrast, more recent studies such as those of Capocci (2005) and Gregoriou et al. (2010) have studied CTAs according to sub-categories reported in BarclayHedge database. Apart from Kazemi and Li (2009), none of these studies have separated CTAs into two main trading styles: systematic and discretionary. In fact, the confusion arises as most CTAs are reportedly trend followers with many CTAs utilizing proprietary trading models to capture trends in the markets using futures. Yet the fundamental difference in the types of funds lies in the way they trade. Systematic CTAs base their trading on technical models and all the execution is automated via trading algorithms. This has been facilitated by an incredible growth in computing power which has had a profound impact on the world of trading; exchanges are becoming electronic, the power of computers continues to improve and the data they generate is becoming more accessible and easily stored. The traders at the frontier of this technological revolution are the systematic or algorithmic CTAs that trade highly liquid, exchange traded instruments. In contrast discretionary CTAs involve a certain amount of human judgement and manager discretion.

The purpose of this chapter is to investigate the performance and persistence of systematic and discretionary CTAs in light of recent market conditions by employing new robust methodologies that are current in the hedge fund literature. Before using CTA data, one must address and minimize biases such as survivorship and instant history biases. These biases are well documented in the literature and arise from the lack of

[2]See http://www.ft.com/cms/s/0/f37adf8e-aeeb-11e1-a4e0-00144feabdc0.htmlaxzz1xPRQ74tf

uniform reporting standards[3]. I update earlier results on the effect of these biases on performance and find that results are consistent with the earlier literature. The performance of the average CTA is investigated on an equal and value-weighted basis after adjusting for these biases.[4] CTAs are found to add value, even after fees, with large systematic CTAs having superior performance to their discretionary counterparts. The value-weighted portfolio, which represents the performance of the overall industry of systematic CTAs delivers higher cumulative returns than many of the market indices. Next, this study examines the ability of CTAs to deliver alpha over the period 1990-2010. By further looking at the performance of funds in the cross-section this study aims to determine if systematic CTAs have more skill than discretionary CTAs. Anecdotal evidence suggests that the lack of emotion and the ability to diversify easily across many markets may allow systematic CTAs to deliver better returns than discretionary funds. Finally, this study aims to answer the question of performance persistence, an issue that has received a lot of attention in the hedge fund and mutual fund literature but has only been addressed with mixed results in the CTA literature[5].

Evaluating the performance and persistence of CTAs is not only complicated by the many biases present in the CTA data, but also by the non-normality of the many CTA return series[6] and the relatively short return histories. These issues have been successfully addressed in the hedge fund literature by employing robust bootstrap and Bayesian methodologies, as proposed by Kosowski et al. (2007) and further used by Fung et al. (2008), together with the GMM approach used by Jagannathan et al. (2010). None of these methods have thus far been applied exclusively to CTAs. Furthermore, Fung et al. (2008) and more recently Bollen and Whaley (2009) have argued that any perfor-

[3]See Fung and Hsieh (1997b), Fung and Hsieh (2000b), Fung and Hsieh (2009), Liang (2000), Malkiel and Saha (2005), Brown, Goetzmann and Ibbotson (1999).

[4]Interestingly a comparative study for CTAs by Bhardwaj et al. (2008) uses equally-weighted index only as the TASS database used in the same study has incomplete AUM information.

[5]For hedge funds see Brown, Goetzmann and Ibbotson (1999), Agarwal and Naik (2000a, 2000b), Edwards and Caglayan (2001), Bares, Gibson and Gyger (2003), Baquero et al. (2005), Kosowski et al. (2007) and Jagannathan et al (2010); for mutual funds see Hendricks, Patel and Zeckhauser (1993), Carhart (1997), Cohen, Coval and Pastor (2005) and Busse and Irvine (2006).

[6]Recent studies by Agarwal and Naik (2004), Gupta and Liang (2005) and Lo (2001) showed that hedge funds have frequently non gaussian return distributions with high skewness and kurtosis.

mance appraisal needs to account for the significant changes in the risk factor exposures of hedge funds since these funds employ dynamic trading strategies and therefore are unlikely to have constant factor loadings. Fung et al.(2008) used a CUSUM test to identify structural breaks in the fund factor loadings at the aggregate level while Bollen and Whaley (2009) argued that a more appropriate approach is to investigate risk dynamics across individual hedge funds since the latter will be representative of managers shifts in allocations across strategies.

The literature on risk dynamics in alternative investments has recently experienced a resurgence of interest. For example, Patton and Ramadorai (2011) propose the use of high frequency conditioning variables to model the dynamics of hedge fund risk exposures. Clearly, estimates of alpha will be inaccurate if the risk exposures of funds change over time and one does not account for it. This study, therefore, investigates the performance of CTAs by first modeling the dynamics of CTA risk exposures. A further issue, highlighted by Titman and Tiu (2010) and by Billio, Getmansky and Pelizzon (2011) is the importance of considering the effect of the financial crisis when studying hedge fund performance. The long data period employed in this study includes several crises, in particular the recent credit crisis of 2008. Using scaled cumulative residuals structural breaks are identified in the CTA factor loadings associated with various market events such as the 1998 LTCM crisis. It is demonstrated that not all structural breaks are the same for CTAs and hedge funds and also that factor loadings are different for systematic and discretionary CTAs. Using these results, it is found that over the sample period of 1994-2010 some of the strategies of systematic CTAs delivered alpha almost consistently in every subperiod whilst many discretionary CTAs had significant alpha only at the end of the sample period.

Using a robust bootstrap methodology the ability of funds to deliver significant alpha in the cross-section is investigated. In particular I find that although the proportion of funds that deliver statistically significant alpha is similar across systematic and discretionary CTAs, the actual alpha is higher for systematic CTAs and the number of funds that subsequently fail are lower. Finally, the performance persistence of systematic and discretionary CTAs is investigated. Evidence of performance persistence for CTAs is found, however this performance persistence differs across CTA strategies. If performance persistence of discretionary CTAs is driven by small funds, the reverse is true for systematic CTAs.

The rest of this chapter is organized as follows. Section 2.2 discusses relevant literature. Section 2.3 describes proposed methodology. Section 2.4 describes the data. Section 2.5 provides empirical results. Finally Section 2.7 concludes.

2.2 Related Literature

According to an earlier study by Brown and Goetzmann (2003) hedge funds are defined by their freedom from regulatory controls. Commodity Trading Advisors, CTAs, are a subset of hedge funds normally listed with the style name "managed futures". CTAs have several features that distinguish them from hedge funds. Firstly they are required to register with the US Commodity Futures Trading Commission, CFTC, and National Futures Association, NFA. In addition, these managers trade in extremely liquid markets, namely in the global futures, forwards and options markets and are able to pass some of the liquidity to their investors. As such, CTAs rarely have long lock ups or redemption periods associated with hedge funds, see Bhardwaj et al. (2008). Assuming that these markets should continue to function in both deflationary and inflationary environments, CTAs should allow investors to speculate in the futures markets in the most dynamic way possible. Furthermore, futures markets are diversified across many asset classes: interest rates, currencies, stock indices and commodities, a feature which provides investors with additional diversification in difficult trading environments. Hedge funds, on the other hand, are free from regulatory controls of the Investment Company Act of 1940, Brown and Goetzmann (2003) and therefore may engage in trading illiquid securities whilst searching for arbitrage opportunities see Getmansky, Lo and Makarov

(2004) thus making them less liquid to CTAs.

CTAs differ from hedge funds in many other important ways and have also been studied for longer in the academic literature, see Elton et al. (1987, 1989 and 1990). Firstly the legal framework of CTAs is slightly different as they are more regulated than hedge funds yet less regulated than mutual funds. Even though they have to register with the CFTC and NFA they are still able to pursue various trading strategies that are unavailable to mutual funds. Since CTAs trade mainly in liquid futures markets they do not have long lock-up and redemption periods frequently associated with hedge fund investing, Getmansky et al. (2004). Fung and Hsieh (1997b) found that CTAs have higher attrition rates than mutual funds. This is also documented by Liang (2003) and Brown et al. (2001) who find the attrition of CTAs to be higher than that of mutual and hedge funds. In the earlier part of this thesis, however, it was found that the attrition rate of CTAs is not as high as previously estimated and, once real failure is taken into account, it is in fact similar to that of hedge funds at only 3%. Getmansky et al. (2004) and Bollen and Whaley (2009) find that the returns of managed futures are not as serially autocorrelated as that of hedge funds, a result of their trading in liquid instruments. CTAs also differ from hedge funds in terms of their trading strategies. Fung and Hsieh (1997) find that CTAs have option like payoffs and that they perform well during market spikes. They propose to model the returns of trend-following funds with a primitive trend-following strategy in various markets (PTFS) and show that these factors are particularly relevant to CTAs[7].

Several papers in the literature examine CTA performance and persistence. Using risk adjusted returns, Bhardwaj et al. (2008) find that CTAs are inefficient, with poor performance over the period 1994-2007, and thus lend support to the earlier study of Elton et al. (1990) who also found that CTAs failed to deliver superior returns. Capocci (2005) finds that some CTA strategies do in fact outperform the EDHEC CTA Global Index. Liang (2004) on the other hand investigates the comparative performance of hedge funds, fund of funds and CTAs and finds that over the 1994-2002 period CTAs

[7] See Fung and Hsieh (2001).

under-performed hedge funds. He also finds that, depending on market conditions, CTAs are negatively correlated to hedge funds and fund of funds because they follow very different trading strategies from those of hedge funds and argues that thus CTAs represent good diversification tool to a portfolio of hedge funds. Using a number of alternative factor models, Gregoriou et al. (2010) find that only a few of the CTA sub-strategies outperform the market during the 1995-2008 period. With regard to the performance persistence of CTAs, an early study by McCarthy, Schneeweis and Spurgin (1996) found some performance persistence during the 1985-1991 time frame. In another study, however, Irwin (1994) found little or no evidence of predictability in average returns. A further study by Brorsen (1998) employed regression analysis and statistical methods and found no evidence of performance persistence. More recent studies by Brown et al. (2001) and Edwards and Caglayan (2001) analysed the performance and persistence of CTAs over the 1989-1998 time frame, reaching similar conclusions. The most recent studies by Capocci (2005) and Gregoriou et al. (2010) used the BarclayHedge database instead of the previously employed TASS database covering the 1994-2008 period and found some performance persistence but noted that it was driven by some of the sub-categories only. The authors pointed to the heterogenous styles across CTAs and suggested that more needs to be done to identify CTA performance drivers and their effect on the analysis of performance persistence. The conflicting results of these previous studies underline the role that a database can play in performance studies. This was recently discussed in Joenvaara et al. (2012).

Performance and persistence have been studied more extensively in the mutual fund and hedge fund literature. Brown, Goetzmann and Ibbotson (1999) used raw and risk adjusted annual returns for offshore funds to find that hedge funds can outperform the market. Other studies include Fung and Hsieh (1997a) and Liang (2000, 2001) who used raw returns to find that hedge fund returns compared favourably to market returns during the bull market of the 1990s. Other authors such as Malkiel and Saha (2005) were rather sceptical of the ability of hedge funds to deliver superior returns. Several authors have also documented that a large part of the variation in hedge fund returns can be explained by market related factors. The relationship is usually non-linear, however, and is best modeled with option based strategies, see Fung and Hsieh (1997a, 2001, 2002 and 2004b) and Agarwal and Naik (2004). Building on this pioneering work, Kosowski, Naik and Teo (2007) and, later, Fung, Hsieh, Naik and Ramadorai (2008) used a bootstrap methodology applied to a cross section of fund returns to identify funds with genuine skill-based alpha from the cross section of fund returns.

The analysis in this chapter builds on this previous work and, in particular, on a number of recent studies that suggest that certain types of funds realize systematically better performance than others. While Titman and Tiu (2010) suggest that these better performing funds are in fact those that load less on factor risk, Heuson and Hutchinson (2011) find that the better performing funds are in fact those with positive skewness, and suggest that investors should account for that in their fund selection. Cai and Liang (2011), meanwhile, through conducting optimal changepoint regression, segregate a cross section of hedge funds into those with dynamic risk exposures and those without, and find that the dynamic funds are associated with better risk-adjusted performance and lower volatilities. This study employs the most recent methodological advances in the hedge fund literature to analyse CTA performance with a particular focus on systematic and discretionary CTAs, employing dynamic factor exposures as suggested in Patton and Ramadorai (2011) whilst allowing for skewness in returns, Heuson and Hutchinson (2011), and controlling explicitly for luck, Kosowski et al. (2007).

The issue of performance persistence is particularly important for hedge funds and CTAs due to the very high rate of attrition of these funds, see Brown et al. (1999), Liang (2000) and Baquero et al. (2005). CTAs in particular have a high attrition rate, as noted, for example, by Baquero et al. (2005): "A large proportion of about 37.4% of the funds with the investment style managed futures have been liquidated by 2000." Much of the theoretical debate on performance persistence in the mutual fund and hedge fund literature has been addressed in reference to the Efficient Market Hypothesis. Economic models, such as that proposed by Berk and Green (2004), predict little or no persistence because much of it is competed away by rational investors that shift capital in search of superior returns. On the other hand, whilst the Efficient Market Hypothesis rules out consistently superior performance, it does not exclude the possibility of persistent under-performance as performance information is not always readily available and requires full liquidity in the investment funds. For hedge funds there are frequently many hurdles to investing, such as longer lock-up periods and redemption notice periods which, in effect, prevent any assets from being withdrawn. Baquero et al. (2005) argue that these share restrictions may cause more performance persistence in a series of hedge fund returns compared to that of mutual funds, and Agarwal and Naik (2000) find that persistence is mostly driven by losers. Since CTAs fall somewhere in between hedge funds and mutual funds in both regulatory framework and structural organization, it is of interest to identify their effect on performance persistence across CTAs. In particular, it is important to identify if systematic CTAs are better able to generate persistently good returns than discretionary CTAs and, in so doing, whether investors are able to identify such funds and rationally allocate capital to them.

In the hedge fund literature, evidence of performance persistence is rather mixed. Brown et al. (1999) find virtually no persistence using annual returns. Agarwal and Naik (2000a) and (2000b) show that the persistence of hedge funds is only short-term in nature (1-3 months). Edwards and Caglayan (2001) find evidence of persistence over a longer horizon 1-2 years. Capocci and Hubner (2004) follow Carhart (1997) and find some persistence across average performing funds. More recent literature on hedge fund performance persistence has addressed well-known biases and data issues that hitherto caused estimation problems. Baquero et al. (2005) examine the persistence of raw and style-adjusted returns of hedge funds in the TASS database for the period 1994-2000 whilst correcting for the look-ahead bias at quarterly, annual and bi-annual horizons. They find that positive persistence is strongest at the quarterly level for both raw and style-adjusted returns whilst being statistically insignificant at the annual level. Kosowski, Naik and Teo (2007) employed the Bayesian approach of Pástor and Stambaugh (2002a), who had applied it to mutual funds. The seemingly unrelated assets (SURA) Bayesian approach is a robust way of modeling misspecification and overcomes the short sample problem of fund return series by using the information from non-benchmark passive returns. Kosowski et al. (2007) show that this methodology is particularly relevant to the study of hedge fund performance and demonstrate that, relative to sorting on OLS alphas, sorting on Bayesian alphas provides evidence of long-term persistence. Boyson (2008) follows the methodology of Kosowski et al. (2007) by sorting on alpha t-statistics and shows that, in addition to sorting on past performance, selecting funds based on age and size improves the likelihood of superior future performance. These results resonate with the Berk and Green (2004) equilibrium: that younger and smaller funds outperform portfolios of older and larger funds, a finding similar to that of Teo (2010), who finds that smaller funds outperform larger funds. Evidence of long-term persistence is also confirmed by Jagannathan, Novikov and Malakov (2010). Their study accounted for look-ahead bias and employed generalized methods of moments, GMM. Using this new approach, they found persistence over a three-year horizon. Most recently, Heuson and Hutchinson (2011) argue that the skewness of hedge fund returns is an important factor for investors and should therefore be integrated into any performance assessment. They demonstrate, using the residual augmented least squares approach, RALS, of Im and Schmidt (2008), that portfolios sorted on RALS alpha persist more than those sorted on OLS alpha. In particular, their study finds that managed futures have a larger number of funds with positive skewness than any other hedge fund strategy. Sorting on RALS alphas is thus particulary relevant to these funds.

Although there is a significant quantity of literature on the performance persistence of CTAs, all of these studies are based on the standard Frequentist performance measures. Gregoriou, Hubner and Kooli (2010) analyze the performance and persistence of CTAs in the BarclayHedge database for the January 1995 to October 2008 period. Using a nonparametric method, they find that certain categories of CTAs have a larger percentage of funds performing above the median. They document evidence of quarterly persistence and find that funds with quarterly persistence are also more likely to be persistent over a longer horizon. In contrast to Kosowski et al. (2007), Gregoriou et al. (2010) find that extreme performance is not an indication of skill and the performance of the top funds tends to revert towards that of the median CTAs. Brorsen and Townsend (2002) use regression analysis and find a small amount of persistence. None of the above studies, however, have employed the more robust methodologies discussed above. Bhardwaj et al. (2008) addressed the well-documented biases in the hedge fund data, survivorship, instant history and self-selection bias and found that CTAs are inefficient performers relative to the market. However, they employed a standard OLS methodology which was shown to be inappropriate to the study of hedge fund returns. To address the dynamic risk exposures of hedge funds, Kosowski et al. (2007) and Fung et al. (2008) identify aggregate structural breaks in hedge fund risk exposures. Closely related to this study is dynamic performance measurement, which is particularly relevant to the study of CTAs. Bollen and Whaley (2009) use optimal change-point regression (à la Andrews, Lee and Plomberger (1996)) which allows risk exposures to shift through time for each hedge fund leading to more accurate performance measurement. Cai and Liang (2011) employ this methodology to identify funds with dynamic and non-dynamic risk exposures and to study the qualities and performance differences across these two categories. More recently Patton and Ramadorai (2011) follow Fernson and Schadt (1996) and propose an alternative method to model hedge fund risk exposures using high frequency conditioning variables and thereby document an increase in alpha for funds with dynamic risk exposures.

This study aims to contribute to the above literature in several ways. First it employs a novel dataset by identifying separate styles across CTAs. This has the advantage of identifying the various characteristics of these funds and helps to isolate performance differences. Secondly, it allows for dynamic risk factors to measure performance, as proposed by Patton and Ramadorai (2011), and explicitly controls for luck by using a robust bootstrap method to identify alpha funds. Finally the study focuses on the performance persistence of CTAs by employing the more robust methodologies used in the most recent hedge fund literature.

2.3 Methodology

A. Risk Adjusted Performance Evaluation

Some performance and persistence studies have used raw as well as risk-adjusted returns, Baquero et al. (2005). Since most investors are risk averse it is unlikely that investors will make investment decisions without considering the risk. Most academic literature on both mutual and hedge funds, therefore, has tended to evaluate the performance of these funds adjusted for risk.[8] The original method used in empirical finance to estimate the abnormal performance of a portfolio is due to Jensen (1968), who applied it to the study of mutual funds. Motivated by the CAPM, Jensen's alpha in this model is the alpha from a regression of a portfolio's excess return on the excess returns of the market:

$$R_{i,t} - R_f = \alpha_i + \beta_i(R_{M,t} - R_f) + \epsilon_{i,t} \tag{2.1}$$

where $R_{i,t}$ is the return of the fund, $R_{M,t}$ is the return on the market index, R_f is the risk free rate and $\epsilon_{i,t}$ is the error term. This is usually used as a measure of out- or under-performance. Further extensions of this basic model were developed by Fama and French (1993) in the three-factor model:

$$R_{i,t} - R_f = \alpha_i + \beta_{1,i}(R_{M,t} - R_f) + \beta_{2,i}SMB_t + \beta_{3,i}HML_t + \epsilon_{i,t} \tag{2.2}$$

where SMB_t is the factor mimicking portfolio for size (small minus big) and HML_t is the factor mimicking portfolio for book-to-market equity (high minus low). The model was further extended by Carhart (1997) by adding the momentum factor:

$$R_{i,t} - R_f = \alpha_i + \beta_{1,i}(R_{M,t} - R_f) + \beta_{2,i}SMB_t + \beta_{3,i}HML_t + \beta_{4,i}UMD_t + \epsilon_{i,t} \tag{2.3}$$

where UMD_t is the factor mimicking portfolio for the momentum effect, which is defined by Grinblatt et al. (1995) as the return from buying past winners and selling past

[8]See recommendation of report of Blake and Timmermann (2003) prepared for the FSA.

losers. Whilst these models have been largely used in the mutual fund literature, none of them seem to explain well the returns of the CTAs, see Gregoriou et al. (2010). Fung and Hsieh (1997b, 2001), for example, have documented that the explanatory power of these traditional asset index factors is particularly low for CTAs and have shown that the returns of the CTAs feature option-like payoffs relative to the return of the underlying assets. This finding motivated them to propose to model the returns of CTAs relative to a dynamically traded portfolio of look-back straddles. Together with equity and bond market factors, these trend-following factors can significantly increase the model's explanatory power for CTAs. As a result of this, a now widely used model for performance evaluation in the hedge fund and CTA literature is the seven factor-model developed by Fung and Hsieh (2004). The Fung and Hsieh (2004) model is as follows:[9]

$$\begin{aligned} r_t^i &= \hat{\alpha}^i + \hat{\beta}_1^i SNPMRF_t + \hat{\beta}_2^i SCMLC_t + \hat{\beta}_3^i BD10RET_t + \hat{\beta}_4^i BAAMTSY_t + \cdots \\ &\quad + \hat{\beta}_5^i PTFSBD_t + \hat{\beta}_6^i PTFSFX_t + \hat{\beta}_7^i PTFSCOM_t + \hat{\epsilon}_t^i \end{aligned} \tag{2.4}$$

where r_t^i is the net-of-fees excess return (in excess of the risk-free rate) of fund i on month t, $\hat{\alpha}^i$ is the abnormal excess return of fund i over the regression time period, that is value added after fees that is not explained by common systematic risk factors. $\hat{\beta}_k^i$ is the factor loading of the hedge fund i on factor k, and $\hat{\epsilon}_t^i$ is the pricing error. The set of factors comprises: the excess return on the S&P 500 total return index (SNPMRF), a Wilshire small cap minus large cap return (SCMLC), the yield spread of the U.S. 10-year Treasury bond over the 3-month T-bill, adjusted for the duration of the 10-year bond (BD10RET), and the change in the spread of Moody's Baa bond minus the 10-year Treasury bond (BAAMTSY). PTFSBD, PTFSFX and PTFSCOM are the excess returns on the portfolios of lookback straddle options on bonds, currencies and commodities, respectively, which are constructed to replicate the maximum possible

[9] The time series of the seven factors can be downloaded from the authors' website: http://faculty.fuqua.duke.edu/dah7/HFData.html

return to trend-following strategies on their respective underlying assets.[10] Fung and Hsieh (2004) show that these factors are able to explain a substantial part of the variation of the hedge fund and CTA return series. Their benchmark model is now the standard workhorse of hedge fund performance evaluation studies.[11] Nevertheless, Gregoriou et al. (2010) build their own option-based factors on eight financial indices to model CTA returns. They further supplement these option-based factors by integrating factor mimicking portfolios for variance, skewness and kurtosis with the addition of Carhart's (1997) momentum factor. Relative to the traditional asset pricing models, their model is able to explain a significantly higher proportion of return variation. An interesting finding however, is that the model is not well adapted to explaining the returns of the discretionary funds. This finding resonates with the conclusion of Kazemi and Li (2009) who augment Fung and Hsieh (2001) PTFS factors with futures return-based factors in order to study the market timing of discretionary and systematic CTAs. Whilst adding futures return based factors significantly increases the explanatory power for systematic CTAs, the adjusted-R^2 remains very low for discretionary CTAs. Bollen and Whaley (2009) argue that although the Fung and Hsieh (2004) model has been widely adopted in the hedge fund literature it is still open to the debate whether these factors indeed represent trading strategies that can be mimicked in the spirit of Carhart (1997) or Sharpe (1992). They, therefore, conduct their study using two models: the Fung and Hsieh (2004) model and the returns of the long positions in the ten liquid futures contracts. Their model also contains a squared term as with the size and value premia:

$$R_{i,t} - R_f = \alpha_i + \beta_{1,i} F_t + \beta_{2,i} F_t^2 + \epsilon_{i,t} \tag{2.5}$$

where vector F contains observations of the returns of a buy-and-hold investment in futures contracts on different assets and rolling the positions as maturities near. They find that, in contrast to the Fung and Hsieh (2004) model, the adjusted-R^2 falls across

[10]Refer to Fung and Hsieh (2001) for the detailed description of the construction of these factors

[11]See Kosowski et al. (2007), Jagannathan et al. (2010), Boyson (2008), Eling (2010), Joenvaara et al. (2012).

all fund categories when the futures contract factors are used. For CTAs, however, the difference in the explanatory power is the smallest but the authors note that the average alpha of CTAs becomes negative when futures contracts are employed. This suggests that performance ranking can be quite sensitive to the choice of factors.

In line with these arguments this study uses the Fung and Hsieh (2004) seven-factor benchmark model, which is the standard workhorse of hedge fund performance studies. Two additional trend-following factors are added, PTFS on interest rates, PTFSIR, and on stock indices, PTFSSTK as well as GSCI index and Carhart (1997) momentum factor. I find that only the GSCI factor is significant and I therefore drop the momentum factor from the model. The final model, therefore, consists of the Fung-Hsieh (2004) seven-factor model augmented with two trend following factors on stocks and interest rates together with the GSCI index.

B. Structural Breaks and Parameter Stability

Static analysis of CTA performance is not appropriate if the funds change their risk exposures over time. Fung and Hsieh (2004, 2008) test the stability of the hedge fund factors with cumulative recursive residuals. Accordingly, they find two structural breaks that they identified with the market events: September 1998 (the LTCM debacle) and March 2000 (the end of the internet bubble). Using these breaks, Fung et al. (2008) apply their model to the fund of hedge funds data in order to estimate the average alpha of the fund-of-funds. In particular, to estimate their model, the authors use dummy variables for the various subperiods. Following their method, I test for the presence of structural breaks in the CTA data. When testing for structural breaks, Fung and Hsieh (2004) argued that, due to the tremendous growth in the hedge fund industry, the older data is less reliable and they therefore ran the regression backwards. CTA data has been available for much longer than hedge fund data. I thus employ a standard method of rolling forwards when testing for regime changes in the CTA data. Regressing an equally-weighted index (with an AUM filter) of CTA returns and a value-weighted index of CTA returns against the F-H 9 factor model, I obtain a time series of scaled recursive residuals. Plotting scaled recursive residuals against time with an error band of ±2 allows the identification of breakpoints by looking at where residuals stray outside these bands. Figure 2.1 plots scaled recursive residuals for the equally-weighted index (with the AUM filter) of CTAs starting from January 1995 and working forwards to December 2010.[12] The two red broken lines represent the confidence bands. The crossing of these bands is evidence of model instability. For the equally-weighted index there are several crossings: June 1996, January 1998, July 1999, end of 2000, March and December 2003 and June 2008. For the value-weighted index the crossing of the bands by the residuals happens on September 1998, end of 2000, Mar 2003 and June 2008. The dates are similar to the results from the equally-weighted index. As discussed in Fung and Hsieh (2004) the actual sample breaks are unlikely to have happened at these exact times since the effect of the sample break shows up gradually in the regression. Instead the authors searched for market events around the time of the sample breaks to pinpoint the actual dates for the breaks.[13] The plots show possible breakpoints to be September 1998 and March 2000, as in Fung and Hsieh's (2008) fund of hedge fund study. The data in this study covers a longer period than that of the Fung and Hsieh (2008) study. I therefore identify another two possible break points: March 2003 and June 2008. I test for the validity of these four breakpoints using Chow's (1960) test, replacing standard errors with Newey-West heteroskedasticity and autocorrelation consistent standard errors. I find that all but one of the breaks (March 2000) are significant. Using these three breakpoints (September 1998, March 2003 and June 2008) I estimate the following regression:

$$R_t = \alpha_1 D_1 + \alpha_2 D_2 + \alpha_3 D_3 + \alpha_4 D_4 + (D_1 X_t)\beta_{D1} + (D_2 X_t)\beta_{D2} + (D_3 X_t)\beta_{D3} + (D_4 X_t)\beta_{D4} + \epsilon_t \tag{2.6}$$

where $X_t = [SNPMRF_t \; SCMLC_t \; BD10RET_t \; BAAMTSY_t \; PTFSBD_t \; PTFSFX_t \; PTFSCOM_t \; PTFSIR_t \; PTFSSTK_t]$

[12]We lose the first 12 months of data for estimation.

[13]In their 2008 study the authors rigorously tested the breaks with the Chow test.

Here, R_t denotes either an equally-weighted index with an AUM filter or a value-weighted index of excess CTA returns across all funds with at least 24 months of data in month t. D_1 is a dummy variable set to one during the first period, January 1994 to September 1998, and zero elsewhere, D_2 is set to one during the second period, September 1998 to March 2003, and zero elsewhere, D_3 is a dummy set to one during the third period, March 2003 to June 2008, and zero elsewhere and D_4 is set to one during the final data period, June 2008 to end of data December 2010, and zero elsewhere. The X matrix comprises the augmented Fung and Hsieh (2004a) model, described above. This framework allows to estimate the average CTA alpha in various subperiods.

2.3.1 Identifying the Factors

Since this study analyzes the cross-sectional differences in the performance of the CTAs, there is another caveat that needs to be dealt with. With the extended model there is a substantial set of possible factors and only a limited number of degrees of freedom. Since the cross-sectional regressions are estimated using only 24 monthly observations, which is the minimum return history required by this study, it is therefore not feasible to include too many factors.[14] My approach is first to select a subset of factors, K, for each CTA so as to maximize the explanatory power of a regression while rewarding parsimony. To achieve this, a few studies have employed a stepwise regression procedure, Gregoriou et al. (2010), Kazemi and Li (2009) as well as Titman and Tiu (2010). This study, however, follows the methodology of Bollen and Whaley (2009) and Patton and Ramadorai (2010) in choosing a subset of factors that minimize the Bayesian Information Criterion (BIC) which is equivalent to maximizing adjusted-R^2.[15] Formally the Bayesian

[14] A minimum 24 month return history is standard practice in the hedge fund literature, see Boyson (2008), Joenvaara et al. (2012) and Kosowski et al. (2007).

[15] Other authors, such as Jagannathan et al. (2010), use SBC Schwarz's (1978) criterion to decide how many factors to include. Bekaert et al. (2008), meanwhile, employs the PCGets algorithm.

Information Criterion can be stated as:[16]

$$BIC(K) = ln\left(\frac{\mathbf{e'e}}{n}\right) + \frac{Klnn}{n} \tag{2.7}$$

where n is the number of observations and K is the number of parameters to be estimated, including the intercept. Once the subset of factors is chosen, I estimate the parameters of the model for each individual fund.

2.3.2 Cross-sectional Bootstrap

Instead of using an index of CTA returns this section seeks to identify cross-sectional differences in CTA performance. To that end this study follows closely the methodology of Fung et al. (2008). In particular I segregate CTAs into those that deliver significantly positive alpha, called "Have-alpha" funds and those that do not and which only take systematic risk, called "Beta-only" funds. To account for the time-varying risk exposures, I implement the sorts on a yearly basis. In particular, each January I select all funds which had a full return history in the preceding two years. For each fund I identify the number of factors, K, from the extended Fung and Hsieh (2004) model by maximizing the Bayesian Information Criterion, as described above. Using relevant factors for each CTA and a bootstrap procedure due to Kosowski et al. (2007), I segregate the funds into those that have statistically significant alpha and those that do not. The bootstrap procedure is particularly useful for CTAs due to the non-normality of their returns. When using standard t-tests to determine the significance of alpha we rely on the assumptions of homoscedastic, serially-uncorrelated and cross-sectionally independent residuals, assumptions that are likely to be violated by the non-normality of the CTA returns and to thus produce an unknown distribution of alpha. The bootstrap allows to relax these assumptions of non-normality while at the same time controls explicitly for luck.

[16]See Greene for further details.

To begin the bootstrap procedure for each fund i, I measure performance relative to the multifactor model. The risk factors are as described before from the extended Fung and Hsieh (2004) model augmented with the GSCI factor. For each fund I estimate the Bayesian Information Criterion that maximizes R^2 to select the relevant number of factors that maximized it. This procedure allowed the selection of different factors for different funds, since many CTAs follow very concentrated strategies in various markets. For example, some CTAs follow a trend-following strategy in currencies only and will therefore have only one trend-following factor that is significant, the PTFSFX. With relevant factors for each fund, I therefore performed the following regression where x'_t represents the relevant risk factors for each fund:

$$r_{i,t} = \hat{\alpha}_i + \hat{\beta}_i x'_t + \hat{\epsilon}_{i,t}, t = 1, ..., T \tag{2.8}$$

For each regression of each fund, I saved the coefficient estimates $\hat{\beta}_i$, $\hat{\epsilon_{i,t}}$, t-statistics of alpha, $\hat{t}_{(\hat{\alpha_i})}$[17] as well as the time series of estimated residuals, $\hat{\epsilon_{i,t}}$. I then draw T periods with replacement from the original time series of $t = 1, ..., T$ and create a new time series of residuals. The order of the time scale will thus change for each bootstrap iteration b. The new time series of residuals can be written as $\hat{\epsilon}^b_{i,t} = s^b_1, ...s^b_T$ where b stands for the bootstrap iteration number. Using newly formed residuals, for each fund I create the resampled monthly net return observations:

$$r^b_{i,t} = \hat{\beta}_i x'_t + \hat{\epsilon}_{i,t}, t = s^b_1, ..., s^b_T. \tag{2.9}$$

This allows to impose the null of zero true performance, i.e. $\alpha_i = 0$ and where $s^b_1, s^b_2, ..., s^b_T$ is the time reordering imposed by the resampled residuals in the bootstrap iteration b. This new sequence of returns has an artificial alpha that is equal to

[17]The $\hat{t}_{\hat{\alpha}}$ was estimated using the Newey-West (1987) heteroskedasticity and autocorrelation consistent estimate of the standard error.

zero. Using the newly estimated returns I then run the following regression:

$$r^b_{i,t} = \hat{\alpha}^b_i + \hat{\beta}_i x'_t + \hat{\epsilon}_{i,t}, fort = s^b_1, ..., s^b_T. \quad (2.10)$$

With the above regression of the bootstrapped returns on the multifactor model, a positive estimated alpha may result since the bootstrap may have drawn an abnormally high number of positive residuals or, equally likely a negative alpha, if the resampling drew an abnormally large number of negative residuals. I save the t-statistics of $\hat{\alpha}^b_i$, $\hat{t^b}(\hat{\alpha}^b_i)$ for each fund. I repeat the above procedure for each fund for $b = 1, ..., B$ iterations, each time saving the t-statistics of alpha. In all the resample tests I set $B = 1,000$. For each fund I therefore obtain the cross-sectional distribution of estimates of the alpha t-statistics $\hat{t^b}(\hat{\alpha}^b_i)$, which result purely from sampling variation since I impose the null of no abnormal performance. For each fund i, if $\hat{t^b}(\hat{\alpha}^b_i)$ is in the upper decile of the distribution of the simulated t-statistics, then the fund is designated a have-alpha fund. Otherwise, the fund is put into the beta-only group.

I repeat the same exercise each year, every time using the most recent two year window of observations for each fund. The two year window for estimation is standard in the literature, see Kosowski et al. (2007) and Jagannathan et al. (2010). Whilst allowing sufficient return data to estimate factor loadings, the 24 months' window also allows to capture the propensity of the funds to change their risk loadings over time, an issue discussed earlier. This methodology will undoubtedly result in the funds classified as have-alpha to change from one period to another depending on their previous risk-adjusted performance, fund liquidations and new entries.

2.4 Data

A few databases track CTA returns, TASS, CISDM and BarclayHedge. In this study, the performance of CTAs is evaluated using monthly net-of-fee returns of live and dead

CTAs reported in the BarclayHedge[18] database between January 1993 and December 2010. This time period spans the bull periods, pre 2000 and 2003-2007, as well as the bear market periods starting with the bursting of the technology bubble in the spring of 2000 and the recent financial crisis of 2008. The BarclayHedge database has perhaps the most comprehensive coverage of the total CTAs in existence. For each individual fund, BarclayHedge provides information on monthly returns (net of management and performance fees), assets under management (AUM), management and incentive fees, lock-up period, strategy classification as well as a brief strategy description and various other information specific to fund characteristics.

BarclayHedge reports two separate databases, consisting of both active "live" and defunct funds, the "graveyard". The graveyard keeps track of the funds that ceased to report to the database because of liquidation or some other reason. To minimize the survivorship bias (discussed further below) I include both the live and the dead funds. As of December 2010 there were a total of 4,048 defunct and live CTAs. To avoid double counting, I removed funds of funds, which left a total of 3916 CTAs with a total AUM of just over US$480 billion under management. The industry coverage is shown in Figure 2.2. The assets under management have grown from just over US$20 billion in 1993 to over US$480 billion at the end of 2010. One important item worth noting is the reversal in the growth of the number of CTAs after 2008, the year of the financial crisis. The recent fall in the number of funds, however, was accompanied by a rise in assets under management. Some funds have clearly liquidated but the remaining funds have received more capital, perhaps as investors began to reallocate to the CTAs in the knowledge of their attractive performance during down markets.

In this dataset I control for a number of potential biases. First, I eliminate duplicate share classes from the same fund family. For example, two funds can appear in the database under the same name and be run by the same fund manager but one will be denoted as "onshore" and the other as "offshore". These are created for regulatory rea-

[18]As shown in Joenvaara et al. (2012) BarclayHedge has the highest number of defunct funds as well as the most extensive AUM coverage.

sons but are virtually identical to each other. Similarly, there can be one fund that is an "LP" and another "Ltd", or "Client" and "Proprietary". There are also many instances of funds that provide multiple share classes denominated in various currencies, such as EUR or GBP, designed for clients who choose to invest in currencies other than US$. These structures are common in the hedge fund and CTA industry where managers set up a master-feeder fund structure, with multiple feeders feeding to the same fund. Another example of duplicate funds is when the same fund appears with the same name twice but one is an older version designed by "Old". Such a fund will have an identical but shorter return history and should therefore be removed. In order to deal with the duplicates I used the following methodology: firstly I identified all the management companies with multiple funds and searched for funds with the same name by string comparison. Thereafter, if their return series had a correlation of 0.95 or more then they were confirmed as duplicates. To decide which duplicates to remove I used either the longest return series or, if the duplicates had an identical length of return series, then I selected the fund with the larger assets under management base. This method is similar to the one employed by Agarwal and Jorion (2010) and Avramov et al. (2011). It is important to emphasize that this procedure would understate the aggregate assets for the manager of the fund with the duplicates that exist side by side with their own respective AUM. Although this is not crucial for the remainder of the analysis, for the purposes of completeness, Figure 2.2 shows total assets in the industry including all the duplicate funds.

Apart from removing duplicates, I also removed funds that report quarterly rather than monthly returns, as well as funds that had missing information. After these extensive filters the total number of funds left was 2798, out of which 728 were live funds and 2070 defunct.

2.4.1 Biases

It is well know that hedge fund and CTA data are not as clean as the mutual fund data and are subject to various biases. These biases are mainly driven by the lack of regulation and the voluntary nature of hedge fund and CTA reporting to the databases. These biases have been extensively studied in the hedge fund literature and to a lesser extent in relation to CTAs. Below is a brief discussion of the potential biases.

Self-Selection Bias - Self-selection bias arises from the fact that reporting in the hedge fund and CTA industry is voluntary and so a fund may choose not to report if its performance is poor. Equally, some very successful funds may never report to the database if they raised capital quickly enough and no longer needed to advertise. Fung and Hsieh (1997b) suggest that these two effects offset each other and thus should limit this bias. Nevertheless, whilst this bias may be an issue for the hedge fund industry, it is less likely to apply to CTAs where capacity constraints are not reached as quickly as for hedge funds.[19] Hence it is possible that self-selection bias is less prominent in the CTA data.

Survivorship Bias - Many databases have started collecting hedge fund and CTA data only fairly recently, around 1994. As a result, many databases do not have any information on funds that liquidated prior to 1994. If the database contains returns of only the surviving funds it can lead to an upward bias in the performance estimates if funds drop out of the database for reasons of poor performance. This bias is known as survivorship bias. Many databases now contain information on defunct funds as part of their database. Most funds that stop reporting are moved to the graveyard. Since reporting in the hedge fund and CTA industry is voluntary, however, some funds may choose not to report for reasons other than liquidation, for example if a fund is closed to new investment. Thus the graveyard may not contain only liquidated/failed funds.

[19]The issue of capacity constraints in the CTA industry is formally addressed in chapter three.

Fung and Hsieh (1997b) estimate the survivorship bias for CTAs at 3.48% per year for the period 1989 to 1995 and 3.6% for the period 1989 to 1997 (Fung and Hsieh (2000)). They measure this bias as the difference in performance between a portfolio of all the surviving funds and a portfolio of all the funds taken together. Similar studies have placed the survivorship bias in the hedge fund industry at 3% per year for 1994-1999, Fung and Hsieh (2000). Similar results were also found by Liang (2000) of 2.24%, Barry (2003) of 3.8% and Ibbotson and Chen (2005) of 2.71%. Malkiel and Saha (2005) however, have found a survivorship bias as high as 4.42%. Rouah (2005) finds a bias of 1.51% for the period 1994 to 2003 when using all exits to the graveyard. However, his estimate of the bias increases to 3.35% when he adds funds no longer reporting to the live funds. Ackermann, McEnally and Ravenscraft (1999) on the other hand, defined the survivorship bias as the difference between a portfolio of surviving and liquidated funds and found a low value of 0.16% per year. Their study, however, covered the 1988-1995 period and therefore does not encompass the period when many funds disappeared from the database. Their suspiciously low survivorship bias has been discussed by Liang (2000). More recently, Bali et al. (2011) found a bias of 1.74% for the period 1994 to 2008 in the TASS database which is the longest period analyzed for the survivorship bias in the hedge fund studies. The most recent update for CTAs has been done by Bhardwaj et al. (2008) who found a survivorship bias for the CTAs in the TASS database of 3.2% for the period 1994 to 2007. This is similar to the previous results of Fung and Hsieh (1997b) and Capocci (2005). I update the results for the survivorship bias using the BarclayHedge database for CTAs. Table 2.1 reports the monthly survivorship bias for the period 1993 to 2009. This is the longest period yet analysed for CTA data. The estimated bias for the entire period is 0.33% per month (3.92% per year). This is in line with previous findings of Fung and Hsieh (1997b) and Bhardwaj et al. (2008) for CTAs and is in line with industry consensus of 3%. A look at the subperiods however reveals that the survivorship bias is much larger before 2000, 5.6%.

In a recent report, Fung and Hsieh (2009) stress the importance of differentiating between truly *liquidated* funds and *missing* funds when estimating the survivorship bias.

Further, the authors note that, in light of the recent financial crisis, the liquidation statistics from this period will be particularly important in estimating the survivorship bias. Using the results from the previous chapter that allowed funds in the graveyard to be separated into truly liquidated funds and those that are still alive or have simply stopped reporting, Table 2.2 reports mean monthly returns for equally weighted portfolios formed using funds broken down by exit type. Table 2.2 shows the returns of the graveyard funds that were identified as either still alive or not reporting. The results show that these funds do indeed have very good returns, with mean monthly returns that are higher than for the surviving funds, 1.35% for the “Alive” group and 1.40% for the “Not Reporting” group vs. 1.29% for the Surviving funds. Liquidated funds have a mean monthly return of 0.63% which is lower than the return of all the graveyard funds. This confirms that the filters employed to sort the graveyard are indeed able to separate the truly failed funds from funds that are still alive or not reporting. Furthermore, these results highlight the importance of separating the graveyard into true failures in the survival studies.

Panel B shows that treating funds that are no longer reporting as live funds increases the survivorship bias to 4.2%. This finding is higher than that found in existing studies. To mitigate the effects of this bias, therefore, for the rest of the analysis this study includes all the funds in the graveyard as well as the live database.

Backfill Bias - The second potential bias in the CTA data is the backfilling bias, also known as “instant history” bias. Funds tend to start reporting to a database only after a period of successful trading, possibly with private capital. Once they start to report to a database, however, they are free to backfill their returns. Since funds are more likely to report to a database following periods of good performance and less likely to report if they had poor performance, this creates an upward bias in the reported performance of both hedge funds and CTA databases. Several studies in the literature have documented the size of this bias. In particular for CTAs, Fung and Hsieh (2000) find a backfill bias of 3.6% for CTAs and Bhardwaj et al. (2008) find a bias of 1.6% if

24 months are removed. Bhardwaj et al. (2008), however, argue that to remove backfill bias entirely one needs to the use first day of reporting to the database as a screen and remove all the data between the start of reporting and fund inception. Unlike the BarclayHedge database, TASS provides both an inception date and the date of first reporting to the database. Using this information, the authors show that for some funds even the most conservative screen, in which 36 months of data is removed, is not enough to remove this bias entirely. Most of the hedge fund literature, however, uses a screen of between 12 and 27 months. In particular, Kosowski et al. (2007) use a screen of 12 months, Gregoriou et al. (2010) use 24 months and Titman and Tiu (2010) use 27 months. Park (1995) estimated an incubation period of 27 months for the MAR CTA database. Brown, Goetzman and Park (1997) also found an incubation period of 27 months in the TASS CTA database but 15 months for hedge funds. This could explain the findings of Bhardwaj et al. (2008) who argue for a larger screen. Consequently, I estimate the effect of backfill bias in the BarclayHedge CTA database using various screens and report the results in Table 2.3. Following the methodology of Park (1995) I estimate this bias as the difference between an average monthly return of a portfolio that invests in all funds in the database and the average monthly return of a portfolio that invests in all funds after deleting the first 12, 24, 36 and 48 months of data for each fund. For the period 1993-2009 the observable portfolio averaged 10.98% per year while the adjusted observable portfolio averaged 8.84% (after deleting the first 12 months of data), 8.57% (after deleting 24 months of data), 7.83% (after deleting 36 months) and 7.91% after deleting 48 months. These results give an estimated bias of 2.14%, 2.41%, 3.15% and 3.07% respectively, which is slightly lower than the bias found by Fung and Hsieh (2000) for TASS CTAs. The results also indicate that the longer the estimation period the higher the bias, although this reverses after 36 months, indicating that it is unnecessary to remove more than 36 months of data. Since a 12 months correction is standard in the hedge fund and CTA literature, to avoid backfill bias, I delete the first 12 months of data in the remaining analysis. In the robustness checks, however, I repeat the analysis deleting 24 months of data.

Return Smoothing - Several studies have showed that the returns of hedge funds exhibit positive serial correlation, see Getmansky et al. (2004). This arises due to hedge funds investing in illiquid securities. Managers are therefore forced to use past prices to estimate returns for their portfolios with illiquid securities. Alternatively, some authors have argued that some funds may purposely smooth the return profile. Lo (2002) shows that smoothed returns result in overstated Sharpe ratios and information ratios. Getmansky et al. (2004) and Loudon et al. (2006) propose models to correct for smoothing in returns. As shown in the literature, however, this issue is not prevalent among CTAs, see Bollen and Whaley (2009). Since CTAs trade in liquid securities only they are unlikely to have smoothed returns. Both Getmansky, Lo and Makarov (2004) and Bollen and Whaley (2009) find that, in comparison to hedge funds and fund of funds, CTAs show very little evidence of serial correlation in returns.

2.4.2 Summary statistics

Table 2.4 Panel A reports for the period January 1994 to December 2010 the cross-sectional mean, standard deviation, median, minimum and maximum statistics for CTA characteristics. This table includes all the funds that were present in the sample without any filters. In this database 27.2% of funds are alive while the rest are in the graveyard. As expected, performance measures are higher for the live funds than for defunct funds: annualized mean return is 12.1% for live funds vs. 8.9% for defunct ones (1.01% and 0.74% monthly). Live funds are also substantially larger than defunct funds with mean assets under management of 155.94 million for live funds and 23.28 million for defunct funds. The average age of the funds are 4.75 years (57 months) which is similar to the results reported in Bali et al. (2011) and in Joenvaara, Kosowski and Tolonen (2012). Since for the main analysis we will need to include the returns of funds with at least 24 months of data, Table 2.4 also shows the number of funds and the proportion with less than 24 months of data. From the entire database, therefore, 567 or 21.2% of funds will have to be excluded. This is quite a substantial loss of information and points to a large number of very young funds.

The payout structure appears to be similar across the funds, with a median management fee of 2% and an incentive fee of 20%. Nevertheless, across both live and defunct funds there are funds that charge as much as a 50% incentive fee. Again this is similar to the results reported in Bali et al. (2011). Another interesting result is the indication for the large size disparity across funds. The mean of the average monthly assets under management is US$59.31 million. Figure 2.3 shows that there are a lot of CTAs in the database that never reached more than US$1 million under management, approximately 19%. In addition 50% of the funds never reached more than US$10 million under management and 62% of the funds never reached more than US$20 million under management. Together with the age statistics this points to a large number of entrants into the CTA industry: there are many funds with very short histories and a very small asset base. Indeed, the barriers to entry into the CTA industry are much lower than for hedge funds due to the large amount of leverage embedded in futures trading. As a result many traders are able to set up on their own and run small trading shops, frequently investing their own assets rather than managing clients' money. It is questionable if these small trading funds should be included in any research as it is unlikely that many institutional investors are likely to invest in these one man operations. To the extent that they represent a large proportion of the CTA database, this raises serious questions for researchers who look at the performance of the CTA industry.

Table 2.4 Panel B displays summary statistics for the sample of CTAs including medians, first and third quartiles of the annualized mean excess return, standard deviation, skewness, kurtosis and maximum drawdown across CTA strategies. The average excess return adjusted for instant history bias across all funds is 3.95% per year, 4.35% for systematic CTAs and 2.58% for discretionary CTAs. Apart from options, all other CTA strategies exhibit positive skewness and kurtosis, indicating a departure from normality of CTA returns. The median maximum drawdown is fairly constant across most strategies, at 20.27% and is much lower than that of the risk factors, indicating the ability of

CTA managers to manage the downside. The last section contains summary statistics for the benchmarks included in the Fung and Hsieh (2004) seven factor model extended with an additional three factors.[20] Table 2.5 shows the correlation across factors. The correlations between factors are low on average, suggesting that multicollinearity is unlikely to be an issue.

Regulation requires all CTAs to register with the NFA as well as the CFTC, after which many funds choose to report to a database. Various studies have applied AUM filters due to concerns that funds with less than a certain level of assets may be too small for many institutional investors, for example Kosowski et al. (2007) remove all funds with less than US$20 million and Boyson (2008) removes funds with less than US$35 million under management. Titman and Tiu (2011) remove funds with less than US$30 million. In the case of the CTA funds such filters will remove more than 50% of the database, which is a large amount of data. Avramov et al. (2011) suggest a dynamic AUM filter which reflects the growth of assets in the entire industry. In line with this reasoning and to avoid removing too many funds, whilst at the same time removing funds that are unlikely to be of serious interest to investors, I apply an AUM filter of US$20 million for funds that existed before 2000 and thereafter an AUM filter of US$35 million. This should preserve as much data as possible whilst removing many small funds. The remainder of the analysis, therefore, will concentrate on those funds that had at least 24 months of data. This yields a total of 2100 funds with a further application of an AUM filter where appropriate.[21]

2.5 CTA Performance

In this section I investigate CTA performance with a particular focus on the differences between systematic and discretionary CTAs. I investigate the average performance of

[20] I thank David Hsieh for making these factors available on his website.
[21] Following Kosowski et al. (2007) the AUM cutoff is implemented every month.

systematic and discretionary CTAs by constructing equally-weighted (EW) as well as value-weighted (VW) portfolios. An important question in portfolio management is whether active fund managers add value on average after fees[22], and this is measured by estimating alpha in regression (2.4). For investors this is of particular interest when deciding whether to allocate to a manager or not. The major interest is whether systematic CTAs deliver better returns than discretionary funds. Contrary to the findings of Bhardwaj et al. (2008) on CTAs, but consistent with the literature on hedge funds (e.g. Kosowski, Naik and Teo (2007)), I find that CTAs add value even after fees. In addition, I find that systematic CTAs deliver superior performance on a risk adjusted basis but this out-performance is driven by large funds. These results hold true even after adjusting for well documented biases in the data.

In order to allow for a sufficient number of observations to calculate the average return I only use funds that contain at least 24 non-missing monthly returns. Another problem is that quite a few funds have a series of zeros at the end of their return stream. These are possibly funds that are not performing well delaying reporting in expectation of imminent liquidation whilst the database vendor fills the gap with temporary zeros. Eventually these funds shut down but never provided the performance for that period. After carefully removing all the zero values at the end of the fund returns and respective AUM numbers and applying the 24 months requirement, the total number of funds reduced to 1942. A few funds also had missing AUM observations but these were very few and, as discussed in Joenvaara et al. (2012), the BarclayHedge database is one of the most complete databases for AUM series. In total there were only four funds that had no AUM, which is a tiny proportion relative to the whole dataset. After removing these funds, the final dataset consisted of 1938 funds. I used excess returns from these 1938 funds to construct an equally weighted as well as value-weighted portfolio with monthly re-balancing. The return series for each portfolio was used to construct Figure 2.4 which shows cumulative excess returns of value-weighted and equally-weighted port-

[22]Previous studies on hedge funds shown that hedge funds add positive values for investors even after fees, see Fung and Hsieh (2004), Kosowski, Naik and Teo (2007)

folios of all CTAs against various benchmarks: S&P 500, MSCI World Index, GSCI, HFRX Aggregate Absolute Return, Dow Jones Credit Suisse Managed Futures Index, Dow Jones Credit Suisse Blue Chip Investable Index, Dow Jones Credit Suisse Hedge Fund Index and Barclays Aggregate Bond Index. Firstly, Figure 2.4 shows that the equally-weighted portfolio has a higher cumulative return than the value-weighted portfolio. Joenvaara et al. (2012) document a similar result for hedge funds and explain that this outperformance may be driven by the better performance of smaller funds, as suggested in Teo (2010). The equally-weighted portfolio, however, marginally underperforms the S&P 500. Both CTA portfolios outperform the other indices, apart from the Dow Jones Credit Suisse Hedge Fund Index (although they outperform the HFRX Absolute Return Index). The large difference in performance between the two hedge fund indices is indicative of the database differences discussed in Joenvaara et al. (2012). Table 2.6 shows summary statistics for the excess returns of the EW and VW portfolios for the aggregate portfolio of CTAs as well as by strategies. Panel A shows the excess returns of the equally-weighted portfolios whilst panel B shows the excess returns of the value-weighted portfolios. The aggregate data indicates that CTAs add value on average. The annualized average EW and VW excess returns are 7.82% and 7.31% per year. These values are quite different to the findings of Bhardwaj et al. (2008) who argue that relative to T-bills, the average value added by CTAs per annum was only 85 basis points. Of interest are the differences between CTA strategies. Whereas the best performing strategy using the equally-weighted index is options[23], which shows an annualized return of 11.16%, systematic CTAs outperform on a value-weighted basis. The excess returns of the value-weighted portfolio of systematic CTAs is 7.08% annualized, versus 4.68% for discretionary CTAs. The highest Sharpe ratio is also achieved by the short-term systematic traders when using the value-weighted portfolio. Figure 2.5 shows cumulative excess returns for equally-weighted as well as value-weighted portfolios for systematic and discretionary CTAs. The value-weighted portfolio for systematic

[23] A result similar to Gregoriou et al. (2010) who also find Options strategy to be the best performing among all CTAs using an equally-weighted index.

CTAs outperforms significantly the value-weighted portfolio of discretionary CTAs but the reverse is true for the equally-weighted portfolio. This underscores the importance of the AUM filter when analyzing CTA performance, given the large number of tiny funds in the CTA database. Contrary to the findings of Teo (2010) and Joenvaara et al. (2012) for hedge funds, this study will demonstrate that for systematic CTAs large funds outperform small funds, as size will serve as a proxy for the research and development necessary to build successful models.

Although the performance of the CTAs found here is substantially higher than the performance documented in Bhardwaj et al. (2008), my findings could be influenced by the instant history bias. In fact Bhardwaj et al. (2008) argue that this is indeed one of the reasons for their finding of negligible CTA out-performance relative to T-Bills. Using information on the funds' inception dates as well as the date of first reporting, they show that even the most conservative screen of 36 months used in academic literature is not enough completely to remove this bias. Park (1995) finds that for CTAs a 27 months' screen is appropriate. However, the differences in the findings of Bhardwaj et al. (2008) could in fact be driven by differences across databases as argued by Joenvaara et al. (2012). Since BarclayHedge does not provide information on the date of first porting to the database, I am unable to perform the same analysis, however I will apply the 12 months screen used in most academic studies.[24] Table 2.7 shows the average excess performance of equally and value-weighted portfolios of CTAs adjusted for instant history bias by using different screens for inclusion of funds in the portfolio. Even after removing 43 months of data the average annualized excess return on an equally weighted portfolio is 5.77%. There is not much difference, however, between a 24 months' screen and a 43 months' screen. The BarclayHedge database on CTAs is substantially larger than the Lipper TASS database used in the Bhardwaj et al. (2008) study. It is possible that the average number of backfilled months is lower in the BarclayHedge database

[24] I also apply a 24 months screen and find that results are not substantially affected: an equally-weighted portfolio of all CTAs delivers an annualized mean return of 6.35% whilst a value-weighted portfolio delivers an annualized mean return of 7.98% which is an increase rather than a decrease in performance.

than in the TASS database. Joenvaara et al. (2012) show that substantially different results can be found in hedge fund studies depending on the database used as the database universes are rarely overlapping. For the remainder of the analysis, therefore, to eliminate backfill bias I will use a 12 months screen. Of interest is that the performance of the value weighted portfolio remains unchanged with a 12 months screen and actually increases with an increase in the length of the screen. Table 2.6 Panel D also shows the average excess performance of equally-weighted and value-weighted portfolios by strategies. A systematic value-weighted portfolio still outperforms discretionary funds, 7.88% vs. 4.26%: a difference that is economically and statistically significant.[25] Although an equally weighted portfolio of discretionary CTAs outperforms systematic CTAs, this difference has diminished and is not statistically significant. It seems that instant history bias has less effect on larger CTAs. The AUM filter may also help to alleviate the instant history bias.

Table 2.6 Panel E presents average performance for the equally weighted portfolio across various size categories and strategies of CTAs. Similar to the findings of Teo (2010) and Joenvaara et al. (2012), the table shows that for the aggregate CTA group performance is related to the fund size. In particular, smaller funds deliver the highest mean annualized return of 7.4% whilst the largest funds, those above US$250 million, had an average performance of 5.47%, a difference of almost 2%. Panels B and C, however, show that the difference in performance between small and large funds in the aggregate sample of CTA funds is driven predominantly by the discretionary CTAs. The difference in average performance between small funds and funds with AUM above US$250 million for discretionary CTAs is 3.29% whereas there is a negligible difference of 0.56% across systematic CTAs. This explains why the cumulative excess return of the value-weighted portfolio of systematic CTAs had a significantly better performance than the equivalent portfolio of discretionary CTAs. The results indicate that, whilst the relationship between CTA size and performance is monotonic for discretionary CTAs, the same does not apply to systematic CTAs. Since institutional investors, and even

[25]Significant at 10% with a p-value of 0.0851 and t-statistics of -1.70.

many high-net-worth individuals, are unlikely to invest into small funds, these funds should be excluded from the analysis and, indeed, such AUM filters have been used in previous academic studies.[26] Recently, Kosowski et al. (2011) propose the use of a dynamic AUM filter instead of a static one to account for the growth of assets in the industry over the years documented in the literature. In line with their argument, I use a filter of US$20 million for those funds with returns prior to January 2000 and a US$35 million filter for those funds with returns from that point until the end of the data.[27] Figure 2.6 shows an equally weighted portfolios of systematic and discretionary CTAs adjusted for survivorship and instant history biases and after applying a dynamic AUM filter. By the end of December 2010 systematic CTAs have gained almost 327% whilst discretionary funds have gained 255%.

In conclusion, the results demonstrate that CTAs do deliver, on average, economically and statistically significant performance. After adjusting for survivorship and instant history biases, between January 1994 and December 2010 the average CTA outperformed T-Bills by 6.51%. This is significantly different to the results reported by Bhardwaj et al. (2008) and may underline difference across databases as reported in Joenvaara et al. (2012).

2.5.1 Risk-Adjusted Performance and Changing Exposures of CTA Indices

Table 2.8 reports results from estimating equation (2.6). The rows list the explanatory variables of the matrix X_t and the columns report the results over the entire period and sub-periods. The bottom panel of the table contains estimates of the Chow structural break test, Chi-square statistics, for the significance of the three structural breaks: September 1998, March 2003 and July 2007. Bali et al. (2011) follow the methodology of Fung and Hsieh (2008) and also find a break in July 2007. Table 2.8 Panel A reports the results using an equally-weighted (EW) index of excess CTA returns with

[26]See Kosowski et al. (2007), Boyson (2008) etc.
[27]I implement the AUM cutoff every month.

a dynamic AUM filter of US$20 million and US$35 million. Table 2.8 Panel B reports the parallel results for the value-weighted index (VW). I use the Chow test to test for the structural breaks identified earlier. The χ^2 statistics in both tables show that the March 2000 break is not significant whereas those in September 1998, March 2003 and in particular November 2007 are significant. For the value-weighted index March 2003 break is more significant than September 1998 or November 2007. In unreported tests, the model without GSCIRF shows an even stronger rejection of the null of no breaks. This result is in contrast to the hedge fund literature that identified two major breaks in the hedge fund data: September 1998 and March 2000. CTAs are known to perform particularly well when the rest of the asset classes are not, Liang (2004), therefore it is likely that CTAs may have different breaks to hedge funds. March 2003, in particular, marks the beginning of the Iraq war and of the policy of rate cuts by the US Federal Reserve, as well as the end of the stock market decline following the bursting of the technology bubble. This was perhaps a period of major trend reversals aided in part by Federal Reserve's quantitative easing. A similar break occurred later following the July 2007 housing bubble crush. The stock market began to decline sharply since its October 2007 highs, followed by a period of rate cuts by the Federal Reserve. CTAs appear to be particularly influenced by the Federal Reserve's monetary policies and unexpected government interventions, since trends tend to reverse abruptly in such circumstances.

The results of both tables indicate that the average CTA has delivered a positive and statistically significant alpha over the entire period from January 1994 to December 2010. For the equally-weighted and value-weighted indices monthly alphas are significant at 1% with values of 0.61% and 0.88%, respectively, with adjusted-R^2 of the regression at 0.382 and 0.321. These low values of adjusted-R^2 indicate that a lot of the variance still remains unexplained by the current model. However, R^2 increases to 0.518 and 0.489 for the regressions with structural breaks, underscoring the importance of identifying time variation in factor loadings when evaluating risk adjusted performance of CTAs. Similar conclusions on the importance of dynamic modeling of the CTA risk factors were documented in Patton and Ramadorai (2011) and Bollen and Whaley (2009).

Table 2.8 Panel A and Panel B show the variation in risk exposures during subperiods. For example, the coefficient on SNPMRF is not significant for the entire period but is highly significant for the period beginning April 2003 to November 2007. For the VW index all the trend-following factor coefficients are significant in the full period but show variation in significance in the subperiods.

Whilst the results for the entire period show that the average CTA delivered a statistically and economically significant alpha, the results with structural breaks for the equally-weighted index show the exact period when this alpha was. The results show that the average alpha was economically and statistically significant only in the first and last periods: January 1994 to September 1998 and August 2007 to December 2010. The results for the value-weighted index are similar. Both of these results, however, are exactly opposite to the results reported in Fung et al. (2008) for the fund-of-funds who find a statistically significant alpha only in the bull period of October 1998 to March 2000. Nevertheless, the results reported here are still consistent with the current literature on CTAs, that finds that CTAs tend to perform well when hedge funds and other asset classes do not. Fung et al. (2008) argue that the hedge fund industry may be heading towards zero alpha, as supported by the absence of any significant alpha in their findings after March 2000. My results for CTAs, however, show that significant alpha is found before September 1998 and after the recent financial crisis, despite the recent growth in assets. This underscores the need to separate CTAs from hedge funds in performance studies.

Before discussing the differences between systematic and discretionary CTAs, it is interesting to note the differences in the above results between value-weighted and equally-weighted indices. Alpha is statistically and economically significant in two subperiods for the VW index whereas it is lower in magnitude and significant in only one subperiod for the EW index. Since large funds will have a larger weighting in the value weighed index this points to the cross-sectional variation in alpha generation between funds of different size. It may also suggest that there are CTAs in the sample that are consistently able to generate alpha. The next section on bootstrap and performance persistence will further explore this issue.

Finally, it is important to address differences between systematic and discretionary CTAs. In unreported tests, using the Chow test for structural breaks, I find that systematic CTAs have the same breaks as for the full CTA sample. Discretionary CTAs, on the other hand, appear to have fewer breaks. Using an EW index of discretionary CTAs I find that the March 2000 and July 2007 breaks are significant, but with a VW index of discretionary CTAs only the November 2007 break is significant - this is also supported by Figure 2.1C. Table 2.9 reports the results of regression (2.6) of an equally-weighted index with an AUM filter by investment objective. Panel A reports the results for the entire period. On average, systematic CTAs deliver an economically and statistically significant monthly alpha of 0.73%, whilst discretionary CTAs deliver an alpha of 0.38%. Looking at sub-strategies further shows that the best performers among systematic CTAs are medium-term trend followers with a monthly alpha of 0.83%, significant at 1%. Fundamental discretionary funds appear to be the worst performers among discretionary funds, monthly alpha of 0.23%. Of interest are the differences in structural breaks between systematic funds. Panel B shows the results of regression (2.6) by investment objective with three structural breaks (September 1998, March 2003 and July 2007). Firstly, adjusted-R^2 increases for systematic CTAs using this model. The adjusted-R^2 does not increase much for the discretionary CTAs, indicating no improvement for the model with these breaks. Regarding monthly average alphas, almost all systematic sub-strategies have positive and statistically significant alphas in the three subperiods, with short-term trend-followers delivering significant alpha consistently throughout the whole period. Discretionary CTAs show significant alpha only in the last period and some in the third subperiod leading up to the financial crisis of 2007. Panel C also reports the results of regressing discretionary CTAs on a model with two structural breaks identified earlier with the Chow test (1987), i.e. March 2000 and November 2007. Using this model there is an improvement in adjusted-R^2 from 0.24 to 0.28 for the entire discretionary CTAs index. The results show that discretionary CTAs behave differently to systematic CTAs and have achieved economically and statistically significant alphas from April 2000 to end of December 2010.

In conclusion, the results above underscore differences between hedge funds and CTAs and in particular differences between systematic and discretionary CTAs. Systematic CTAs have different structural breaks to hedge funds, March 2003 but not March 2000, and they also deliver statistically and economically significant alphas when hedge funds do not. This result has been documented earlier for CTAs but not specifically for systematic CTAs. Furthermore, the results suggest that there exist differences between systematic and discretionary CTAs: not only do systematic CTAs deliver superior returns but they also appear to deliver significant alpha consistently throughout the entire period. The current model does not explain much of the variance of the discretionary CTAs, adjusted-R^2 are much lower than for systematic CTAs. Finally, contrary to the conclusion of Fung and Hsieh (2008), the alpha of systematic CTAs does not seem to be heading towards zero.

2.5.2 Cross-Sectional Differences in Funds

This section studies the cross-sectional difference in funds among systematic and discretionary CTAs. Table 2.10 Panels A and B show the results of the bootstrap experiment for each two year classification and holding periods together with the percentage of the total number of funds that were classified as have-alpha or beta-only funds.[28] Table 2.10 Panel A shows the results for systematic CTAs while Panel B shows the results for discretionary CTAs. Similar to the findings of Fung et al. (2008), the number of funds in both groups increases steadily over time. Fung et al. (2008) argue that this is a reflection of the increased availability of data and the growth in the CTA industry. Despite the negative publicity associated with CTAs, the number of funds has continued to grow. My results are similar to the findings of Fung et al. (2008), in that a larger share of funds is classified as beta-only funds than have-alpha funds. Whilst the average proportion of have alpha funds for the period 1994-2003 is 0.22 in the Fung et al. (2008)

[28]Only funds with full two year return histories were included in the analysis.

study, my results document a higher proportion for the systematic funds, 0.33%. This proportion fluctuates from year to year, but the average appears to be driven by the increase in the proportion of have alpha funds in the last three years, 2007-2010. The results also show a decrease in the proportion of have alpha funds following the 1998 LTCM crisis and in 2003-2004 after possible trend reversal. These results are consistent with the earlier findings of the structural breaks. For discretionary CTAs, the proportion of have-alpha funds fluctuates less, indicating less sensitivity to the market conditions. This is in line with the findings of Table 2.9 which shows no firm evidence of significant alpha until after 2007. Interestingly, the proportion of discretionary have-alpha funds increases to 0.48% in the 2009-2010 period. I also document the average alpha of have-alpha and beta-only funds. Whilst the proportion of have-alpha funds is not that different between systematic and discretionary CTAs, my results highlight that the values of alpha obtained by those have-alpha funds are significantly and economically higher for systematic funds than discretionary.

The two year transition period results show that systematic have-alpha funds have less probability than discretionary funds of subsequently being reclassified as liquidated or failures. More of them are likely to be classified as funds that stopped reporting. The results also show that more of the have-alpha funds from both groups are subsequently reclassified as have-alpha funds: that is there is greater persistence among this group of funds. What is of particular interest is that for those have-alpha funds that are subsequently reclassified as have-alpha funds the average fund size is over US$1 billion for systematic CTAs but only US$275 million for discretionary CTAs. That is, performance persistence for these funds is driven by large funds. In summary, the results of this section further confirm that in the cross-section of CTAs there exist funds among both systematic and discretionary CTAs that are able to deliver significant alpha. Moreover this proportion is larger than that documented for fund of hedge funds indicating more skill among CTAs. In addition, whilst systematic and discretionary CTAs have similar proportions of have-alpha funds, the systematic have-alpha funds deliver statistically significant higher average alpha. These have-alpha funds have a propensity to deliver alpha in the future and for systematic CTAs it appears to be driven by larger funds.

2.6 Performance Persistence

In this section I study performance persistence among CTAs, both as an entire asset class and by the CTA strategies identified earlier, while correcting for backfill, serial correlation and survivorship biases in the data. When investors are seeking to invest in a CTA, is the prior performance record useful in making investment decisions? If so then past performance is indicative of future results and such information is valuable. Predictability and persistence are slightly different concepts however. Persistence implies that there is a positive correlation between past and future performance. When the abnormal performance is due to skill then funds maintain their relative positions in the rankings in the two periods. For investors, performance persistence is important for several reasons. Investors investing into hedge funds face restrictions on capital withdrawals in the form of long lock-up periods, redemption notice periods and advance notification periods.[29] All these restrictions make it impossible for investors to withdraw their capital easily and in such circumstances long-term performance persistence becomes important. Few CTAs, however, impose restrictions on capital withdrawals since most engage in trading the most liquid instruments, futures. For investors investing into CTAs, taking advantage of the liquidity becomes especially interesting since an investor can potentially increase the returns to his portfolio by buying past winners with frequent re-balancing. Thus short-term persistence for CTAs potentially has some value.

Research on performance persistence is quite extensive in the mutual fund and hedge

[29] Some hedge fund strategies such as Merger Arbitrage for example, impose long lock provisions (sometimes up to a year). In such instances investors are not allowed to redeem or sell shares. The lock-up period helps the manager avoid liquidity problems when his capital is allocated to illiquid investments. At the end of the lock-up period investors are able to redeem their shares by giving advance notice and then waiting for the redemption period to end before receiving their capital. According to Joenvaara et al. (2012) up to 25% of hedge funds impose a one year lock-up period, although periods of two years or more have become more common in recent years as well.

fund literature. For mutual funds the literature documents very limited evidence of performance persistence. Hendriscks et al. (1993) and Grinblatt and Titman (1992) show only short-term persistence for mutual funds whilst Carhart (1997) attributes any short-term persistence to momentum. Literature on hedge funds and CTAs, meanwhile, has provided somewhat mixed evidence on performance persistence. For hedge funds, nearly all authors have found short-term performance persistence but mixed results for long-run performance persistence. Using the return on a hedge fund in excess of the average return earned by all the hedge funds following the same strategy as a measure of performance, and employing parametric and non-parametric tests for performance persistence, Agarwal and Naik (2000a, 2000b) find evidence of significant quarterly persistence but no semi-annual or annual persistence.[30] Edwards and Caglayan (2001) test for annual persistence and find that it holds for losers as well as winners. Brown, Goetzmann and Ibbotson (1999), on the other hand, use annual data to study the performance of off-shore hedge funds and find little persistence. Similarly Bares, Gibson and Gyger (2003) use an eight-factor APT model and find persistence at monthly and quarterly horizons only. Recently, however, using sophisticated econometric approaches, some authors have found evidence of long-term persistence in hedge funds. Jagannathan et al. (2010) employ a parametric approach whilst correcting for look ahead and backfill biases and serial correlation by utilizing GMM estimation, and find evidence of performance persistence for a three year interval. Contrary to the findings of Edwards and Caglayan (2001), Jagannathan et al. (2010) show that there is performance persistence among winners but not among losers. Joenvaara et al. (2012) explain that the difference in the results of different studies are a consequence of using commercial databases rather than the aggregate of all databases. Following standard Carhart (1997) methodology and sorting on t-statistics, the authors show that there is indeed annual performance persistence but only for the aggregate of all databases rather than individual ones. Similarly to Boyson (2008) they find that persistence is driven by small funds. Kosowski et al. (2007) follow

[30] The authors use a cross-product ratio (CPR) test as well as the Chi square test due to Carpenter and Lynch (1999) as the non-parametric method and regression based method.

the methodology of Carhart (1997) together with Bayesian techniques and find that the performance of hedge funds persists at annual horizons.

Literature on CTA performance persistence is not as extensive as that on hedge funds particularly with regard to methodologies applied. The earliest studies Irwin, Krukemeyer and Zulauf (1992b) and Irwin (1994) find no evidence of performance persistence. Schneeweis, Spurgin and McCarthy (1997) find small amount of persistence but their sample was very small, 56 funds. Most of these studies used Elton, Gruber and Rentzler (1990) method that ranked funds by their mean return or Sharpe ratio and then determined whether funds that ranked high in the first period also ranked high in the next. Brown, Goetzmann and Park (2001) used non-parametric approach and also found no evidence of performance persistence for CTAs. Using regression analysis and Spearman's rank correlation test, Brorsen and Townsend (2002) were the first to document performance persistence for CTAs. The most recent study by Gregoriou, Hubner and Kooli (2010) used the largest period studied to date to analyze performance persistence of CTAs. Although the study finds short-term persistence and limited long-term persistence these results are shown to vary greatly from one CTA category to another.

When testing for performance persistence one can test for statistical predictability or economically significant predictability or both, Cuthbertson et al. (2006). Statistical measures of persistence will rank funds based on some risk adjusted performance measure over some past horizon and then measure the association between past performance and future performance. Examples are regressions of pre and post-alphas as employed in Jagannathan et al. (2010). Similarly, tests based on contingency tables, e.g. Cross-product ratio (CPR) or Chi-square statistics as in Agarwal and Naik (2000a), involve frequency counts of repeat winners and losers in two consecutive periods. Whilst these methods measure the degree of persistence from a statistical point of view, one cannot directly assess the economic significance of predictability. Another popular method to test for persistence, which is employed in this study, is the frequentist approach of recursive portfolios due to Carhart (1997). This method allows to test both for statistical predicability whilst at the same time providing a way to measure the economic significance of the results. This methodology was used in the studies by Kosowski et al. (2007), Boyson (2008), Hendricks, Patel and Zeckhauser (1993) and Joenvaara et al. (2012). First, a sorting rule is established. Whilst in theory sorting may involve any rule that separates the funds into future "winners" and "losers", the most commonly used metric is the risk adjusted performance. Kosowski et al.(2007) advocate the use of alpha t-statistics, which is equivalent to sorting on information ratio. Sorting on the t-statistics of alpha reduces the sensitivity of estimates to outliers as well as serving to correct for errors in alpha measurement that are due to the short time series of CTA data. Specifically, each January I sorted the portfolios into decile portfolios based on their t-statistics of alpha obtained from the extended Fung and Hsieh (2004) model.[31] To obtain estimates of alpha, however, for each fund I first identified K number of factors from the extended Fung and Hsieh (2004) model that maximized the adjusted-R^2 using the Bayesian Information Criterion. Using K number of factors for each fund I then estimated alpha t-statistics. This process was repeated each January for the January 1994-December 2010 period. I used funds that had at least 24 months of returns in the last two years prior to the formation period. Once formed, portfolios were held for a period of either 3 months, 6 months or one year. The post-ranking portfolio returns were re-balanced monthly so that the weights were adjusted whenever a fund disappeared. CTAs with the highest t-statistics of alpha comprised Decile 1 and those with the lowest t-statistics of alpha comprised the bottom decile. I also calculated the spread return of the top and bottom portfolios defined as Decile 1 - Decile 10. A significant difference in the spread return is evidence of performance persistence during the selected evaluation period. To understand the drivers of performance persistence better, which is particularly important for systematic CTAs, I constructed value-weighted as well as equally-weighted post-ranking portfolios.

The overall results of this study show that CTA performance persists for both systematic and discretionary CTAs, but there are important differences between the two.

[31] For some strategies, due to the small amount of data, I used quintiles or terciles. Where appropriate I marked in the results which strategies used which method.

Table 2.11 shows the results of sorting funds into decile portfolios on the basis of OLS alpha and t-statistics for the aggregate CTA database. Table 2.12 shows the results for the quintile portfolios for systematic and discretionary CTAs. Both tables show that ranking on t-statistics of alpha produces a higher spread than when ranking on OLS alpha - perhaps a result of the improvement in precision obtained from sorting on the t-statistics. Results are broadly consistent with Kosowski et al. (2007) and Joenvaara et al. (2012). For the annual evaluation period, the results show evidence of statistically significant persistence for all CTAs.[32]. Overall, the results show evidence of performance persistence for the aggregate database of all CTA funds. Using t-statistics of alpha to sort portfolios into deciles produces a spread of 5.26% with a t-statistic of 2.26. According to this result an investor can increase alpha by buying the top decile funds and avoiding the bottom decile funds by using alpha t-statistics. Results for the discretionary and systematic CTAs show a different picture. Whereas discretionary CTAs show evidence of performance persistence with a spread of 8.12%, when sorting on alpha t-statistics the spread of systematic CTAs is only 2.38% and is not statistically significant. These results do not hold for the value-weighted portfolios, however.

Table 2.13 shows the results of the equally-weighted and value-weighted CTA performance persistence test. The table reports annualized Fung and Hsieh (2004) ten factor alpha and the t-statistics of alpha below for the top portfolio, bottom portfolio and the spread. The results are shown for portfolios that were held quarterly, semi-annually and annually. There are striking differences in the estimates between systematic and discretionary CTAs. Discretionary funds show evidence of performance persistence for both the equally-weighted and the value-weighted portfolios, however their performance persistence is driven by small funds as the spread is higher for the equally-weighted portfolio than for the value-weighted one. This is similar to the findings of Joenvaara et al. (2012) and Boyson (2008) for hedge funds. For example, for a three month evaluation period the spread for the equally-weighted portfolio is 9.74% significant at 1%. For

[32]Due to the lower number of funds for the sub-strategies I sort the funds into quintile portfolios instead of decile portfolios.

the same evaluation period, however, using the value-weighted portfolio the spread decreases to 6.28% and for the 12 months' evaluation period it decreases further to 5.07% and is not significant. Thus performance persistence of discretionary CTAs is driven by small funds. This is similar to the results in the literature on hedge funds. Teo (2010) shows that small hedge funds outperform large funds and Joenvaara et al. (2012) show that hedge funds persist but this persistence is driven by small funds only. For systematic CTAs results are strikingly different. As a group systematic CTAs show significant performance persistence only for the value-weighted index with a spread of 10.52% with a t-statistic of alpha of 2.87. Most interestingly this spread is driven mainly by short-term and medium-term trend followers. Short-term trend-followers have a spread of 12.74% significant at 1% for the annual formation period. These funds also have significant persistence for the equally-weighted index but the results are lower. Medium-term trend-followers also show significant spread for the annual horizon but not for quarterly or semi-annual. None of the other systematic strategies show evidence of performance persistence. In the mutual fund literature Hendricks et al. (1993) also document more evidence of long-term rather than short-term persistence with persistence being highest at two year horizon. Finally, Options funds show negative spread indicating no persistence for any period. Discretionary funds that use relative value strategies have a significant spread of 11.88% with quarterly rebalancing, but this spread diminishes and becomes insignificant at semi-annual and annual horizons.

To confirm that performance persistence is driven by the assets under management of CTAs I perform separate sorts on fund size, with results reported in Table 2.14. Funds were sorted into terciles based on their prior period mean assets under management and held for one year or six months. An important aspect of this method is that it is cross-sectional. Therefore if a fund has attracted more capital and grew larger in one period it would be moved into another tercile in the next period and replaced by another smaller fund. This test follows closely the methodology of Boyson (2008) which was designed intentionally to test the predictions of the Berk and Green (2004) model. In their model Berk and Green (2004) argue that investors rationally allocate capital to funds that perform well, which in turn increases their size and subsequently leads to lower performance as managers face capacity constraints. If this model holds then performance persistence should decrease as fund size increases, argues Boyson (2008), because as funds grow they face fewer investment opportunities and higher transaction costs. The Berk and Green (2004) model was written to describe the mutual funds industry but literature on hedge funds shows that the implications of the model may also hold for hedge funds. Fung et al. (2008) show evidence of capacity constraints for funds of funds and Boyson (2008) documents that size matters for performance persistence. My results for discretionary CTAs are in line with those found in the hedge fund literature: large funds underperformed small funds in the 1994-2010 period by 2.91 per annum for the one-year evaluation period and by 3.45% for the six months holding period. The results are similar to those found in Boyson (2008). For systematic CTAs however, large funds significantly outperformed smaller funds by 3.46% for the one-year holding period and 2.75% for the six month holding period. This finding indicates that systematic CTAs face lower capacity constraints than discretionary funds. This has important implications. First of all, from a theoretical point of view, these results for systematic CTAs challenge the general conclusions in the hedge fund literature that suggest that the industry is experiencing diminishing alpha due to capacity constraints. My results show that this is not the case for systematic CTAs. Secondly I show that the performance of CTAs persists but this persistence varies significantly across strategies: the persistence of discretionary CTAs is driven by small funds, whereas that of systematic CTAs is driven by large funds. CTAs pursuing options strategies show no persistence at any horizon. These results have important implications for institutional investors. Institutional investors face minimum capital constraints and therefore, for many, investing into small funds may be unrealistic. My results demonstrate that, unlike for hedge funds, institutional investors can increase the returns to their portfolios by investing into large systematic CTAs from a top decile and that capacity constraints among systematic CTAs are not as severe as for the rest of the hedge fund industry.

2.7 Conclusion

In this study, I employ a novel dataset on CTAs to investigate performance, risk and performance persistence of CTAs over the longest period studied in the CTA literature, 1993-2010. Firstly I update and extend the results on the effect on performance of data biases. In contrast to previous findings, however, I find that even after correcting for these biases, the average CTA is able to add value after fees. These results are strongest in particular for large systematic CTAs.

Furthermore, I find that the returns of CTAs are driven by the nine risk factors which are found by extending the seven-factor Fung and Hsieh (2004a) model. This model appears to be better suited to systematic rather than to discretionary CTAs, however, as a large proportion of the variance of the discretionary CTAs remains unexplained by the model. Using these factors I find several structural breaks in the data including one break, March 2003, that is particular only to CTAs. Using these breaks I find that some of the systematic funds were able to deliver statistically significant alpha in every subperiod, whilst discretionary CTAs had statistically significant alpha only at the end of the sample. These averages conceal cross-sectional variations, however. Using robust bootstrap methodology I find that on average 30% of CTAs deliver positive and statistically significant alpha. Although these proportions are similar between systematic and discretionary CTAs, the level of alpha of these alpha funds is higher for systematic CTAs. Furthermore, these alpha funds are less likely to fail in the future with lower failure probabilities for systematic CTAs.

I also investigate performance persistence among systematic and discretionary CTAs. I find evidence of significant performance persistence for the aggregate CTA database at an annual horizon. For the sub-strategies there are important differences however. I find greater performance persistence for discretionary CTAs when using an equally-weighted rather than a value-weighted index, implying that smaller funds drive performance persistence. For systematic CTAs, I find little performance persistence using an equally-weighted index and the largest performance persistence when using a value-weighted index. These results have important implications for institutional investors. Previous findings in the hedge fund literature have found that smaller hedge funds deliver higher performance than larger funds and greater performance persistence. These results are in line with Berk and Green's (2004) equilibrium but will be difficult for institutional investors to exploit due to the capital allocation constraints that they face. My findings, however, show that for CTAs, institutional investors will be able to improve the return to their portfolios by investing into the top decile of large systematic CTAs. These findings challenge the view that CTAs are not able to add value after fees. They also suggest that contrary to the conclusions in the hedge fund literature, systematic CTAs do not appear to be heading towards zero alpha, at least not just yet.

2.8 Appendix

Table 2.1: **Survivorship Bias in CTA Returns**

Table 2.1 reports the survivorship bias calculated from the filtered database containing 2798 funds, including 728 live funds and 2070 dead funds for the period January 1993 to December 2010. In this table survivorship bias is calculated as the difference between an equally weighted portfolio of all the live funds and an equally weighted portfolio of all the funds. All returns are net of all fees. Return is a mean return for the year and the numbers are monthly percentages. Obs. indicates the number of monthly returns used to calculate the mean return for the year.

Year End	**All funds**		**Surviving funds**		**Dissolved funds**	
	Return	Obs.	Return	Obs.	Return	Obs.
1993	1.37	8038	2.32	671	1.29	7367
1994	0.74	8113	0.91	807	0.72	7306
1995	1.41	8046	2.15	988	1.30	7058
1996	1.19	7697	1.90	1127	1.07	6570
1997	1.24	7283	1.43	1215	1.21	6068
1998	1.07	7149	1.63	1432	0.93	5717
1999	0.42	7268	0.59	1736	0.37	5532
2000	1.17	7022	1.42	1989	1.07	5033
2001	0.57	6903	0.75	2211	0.49	4692
2002	1.41	7331	1.61	2547	1.29	4784
2003	1.11	7994	1.46	2849	0.91	5145
2004	0.61	8818	0.81	3425	0.49	5393
2005	0.66	9768	0.82	4340	0.53	5428
2006	0.81	10347	0.96	5299	0.65	5048
2007	1.10	10619	1.25	6392	0.87	4227
2008	1.26	10505	1.60	7530	0.36	2975
2009	0.20	9369	0.27	8445	-0.85	924
Mean 1993-2000	1.08		1.55		0.99	
Mean 2001-2009	0.86		1.06		0.53	
Mean 1993-2009	0.96		1.29		0.75	

Panel B: Surviving funds - All funds

Bias 1993-2000	0.47 per month
	5.61 per year
Bias 2001-2009	0.20 per month
	2.42 per year
Bias 1993-2009	**0.33 per month**
	3.92 per year

Table 2.2: **Table II: Mean Monthly Returns of Live and Dead Funds with Various Exit Types and Survivorship Bias**

Table 2.2 reports mean monthly returns calculated for equally weighted portfolios of funds with various exit types for the period January 1993 to December 2010. In particular, the graveyard funds are separated into liquidated funds, funds that are alive but are closed to new investors, called "Alive" and funds that simply stopped reporting to the database for various reasons, "Not Reporting". The database is filtered to exclude duplicates and contains 728 live funds and 2070 dead funds. Difference in means is the difference between live funds and funds in the graveyard with various exit types. Ann. is the annualized difference in means.

Panel A: Surviving Funds = All Surviving Funds as of Dec 2010

Defunct funds	Live Return	Dead Return	Difference in Means	Ann.
Liquidated + Alive + Not Reporting	1.29	0.75	0.54	6.50
Liquidated + Alive	1.29	0.66	0.63	7.56
Liquidated + Not Reporting	1.29	0.62	0.67	8.04
Alive + Not Reporting	1.29	1.36	-0.07	-0.84
Liquidated	1.29	0.63	0.66	7.92
Alive	1.29	1.35	-0.06	-0.72
Not Reporting	1.29	1.40	-0.11	-1.32

Panel B: Live funds = All Surviving Funds + Alive Funds + Not Reporting Funds

	Live Return	Other Return	Difference in Means	Ann.
All funds	1.31	0.96	0.35	4.20
Liquidated funds	1.31	0.63	0.68	8.16

Table 2.3: **Instant History Bias for CTAs**

Table 2.3 reports the instant history bias calculated for CTAs in the BarclayHedge database for the period January 1993 to December 2010. The database contains 728 live and 2070 dead funds. Instant history bias is calculated as the performance difference between average monthly returns of the observable portfolio, which naively invests in all of the existing funds each month, and of the adjusted portfolio which invests in all the CTAs after deleting the first 12, 24, 36 and 48 months of returns. All returns are net of all fees.

	Mean Annual Return	Difference	Average no. of funds
All	10.98%		710
Without 12M	8.84%	2.14%	563
Without 24M	8.57%	2.41%	436
Without 36M	7.83%	3.15%	335
Without 48M	7.91%	3.07%	288

Table 2.4: **Descriptive Statistics**

Table 2.4 reports descriptive cross sectional statistics for the entire database of CTA returns prior to application of instant history bias filter. This table shows the descriptive statistics for the 728 live, 2070 dead funds as well as for the entire group as of December 2010. The table reports the number of funds, the cross-sectional mean, standard deviation, median, minimum and maximum for CTA characteristics including return, size, age, management and incentive fees.

Panel A:

Live and Dead	No. of funds	Mean	Stdv	Median	Min	Max
Average monthly return	2677	0.81	1.65	0.63	-16.27	21.16
Average monthly AUM in millions	2672	59.31	458.48	4.2	0.004	13230.38
Age of the fund	2677	57	46	43	2	216
Management fee	2677	1.96	1.08	2	0	6
Incentive fee	2677	20.39	4.52	20	0	50
Funds with less than 24 months data	567	0.53	2.62	0.44	-20.89	19.57
Live	No. of funds	Mean	Stdv	Median	Min	Max
Average monthly return	728	1.01	1.23	0.84	-5.02	9.77
Average monthly AUM in millions	726	155.94	862.02	11.63	0.01	13230.38
Age of the fund	728	83	60	64	3	216
Management fee	725	1.72	0.74	2	0	5
Incentive fee	725	20.64	4.76	20	0	50
Dead	No. of funds	Mean	Stdv	Median	Min	Max
Average monthly return	1949	0.74	1.78	0.54	-16.27	21.16
Average monthly AUM in millions	1947	23.28	83	2.98	0.004	1423.28
Age of the fund	1949	48	35	37	2	199
Management fee	1950	2.06	1.28	2	0	6
Incentive fee	1950	20.31	4.43	20	0	50

Table 2.4 Continued: Descriptive Statistics

Table 2.4 Panel B reports descriptive cross sectional statistics for the filtered database of CTA adjusted for instant history and survivorship bias, i.e. including all the dead funds and after removing the first 12 months of data for each fund. The top part of the table reports, for each investment category, the number of funds, the cross-sectional median as well as first and third quartiles in parentheses of the annualized mean excess returns over the risk free rate, standard deviation, kurtosis, skewness and maximum drawdown. These statistics are computed using monthly net of fee returns of CTAs in the BarclayHedge database for the period January 1994 to December 2010. The last section of the table reports the same statistics for the factors used in the remainder of the analysis.

Panel B:

CTA Excess Returns Without Survivorship and Instant History Bias Without 12m	**No. of funds**	**Mean (Ann.)**	**Stdv (Ann.)**	**Skewness**	**Kurtosis**	**Max Drawdown %**
SYSTEMATIC	1010	4.35 (-0.79, 9.73)	15.96 (10.64, 23.39)	0.32 (-0.11, 0.76)	4.12 (3.28, 5.46)	21.04 (12.99, 32.51)
Short-Term	181	2.50 (-1.19, 8.76)	11.55 (6.41, 18.59)	0.20 (-0.26, 0.74)	4.62 (3.58, 6.01)	14.86 (9.26, 24.12)
Medium-Term	542	4.54 (-0.64, 9.98)	16.45 (11.99, 23.64)	0.38 (-0.01, 0.81)	4.07 (3.25, 5.32)	21.75 (14.25, 32.76)
Long-Term	138	6.73 (0.93, 12.15)	21.74 (15.62, 33.00)	0.42 (0.06, 0.84)	4.00 (3.24, 5.68)	29.32 (19.99, 44.78)
Spread/RV	77	1.75 (-1.54 , 4.67)	12.13 (7.83, 16.07)	0.04 (-0.45, 0.47)	3.94 (3.13, 4.97)	17.49 (8.39, 21.82)
Counter Trend	11	4.41 (1.26 , 7.25)	15.60 (11.88, 17.12)	0.30 (-0.41, 0.45)	4.43 (3.57, 5.41)	20.78 (12.39, 39.64)
Pattern Rec	61	4.91 (0.52 , 11.98)	16.83 (9.40, 23.30)	0.33 (-0.15, 0.57)	3.76 (3.06, 5.34)	18.36 (10.96, 30.67)
DISCRETIONARY	430	2.58 (-1.81 , 10.38)	13.71 (7.30, 23.85)	0.48 (-0.18, 1.13)	4.87 (3.68, 7.17)	17.07 (8.58, 34.93)
Fundamental & Technical	138	2.62 (-1.13 , 12.35)	14.27 (7.27, 28.62)	0.59 (-0.15, 1.23)	5.25 (3.81, 7.38)	17.15 (8.82, 37.72)
Fundamental	99	1.25 (-2.56 , 5.46)	13.49 (7.17, 23.14)	0.35 (-0.18, 1.05)	4.72 (3.74, 7.27)	17.57 (10.27, 34.69)
Technical	156	3.63 (-2.04 , 10.44)	14.03 (7.28, 26.99)	0.53 (-0.07, 1.14)	4.68 (3.54, 6.69)	17.07 (7.15, 35.45)
Spread/RV	37	2.76 (0.34, 11.26)	10.77 (4.92, 17.96)	0.16 (-0.78, 0.85)	5.36 (3.71, 8.18)	11.72 (6.23, 22.15)
OPTIONS	91	5.58 (0.13, 12.01)	20.10 (10.78, 28.95)	-1.44 (-2.81, -0.04)	10.23 (5.27, 18.36)	27.86 (12.95, 46.56)
ALL FUNDS	1531	3.95 (-1.00, 9.99)	15.33 (9.63, 23.83)	0.32 (-0.19, 0.84)	4.39 (3.39, 6.25)	20.27 (11.80, 34.12)

Risk Factor Returns	**Mean (Ann.)**	**Stdv (Ann.)**	**Skewness**	**Kurtosis**	**Max Drawdown %**
Equity Market	4.41%	15.70%	-0.69	0.95	56.08
Equity Size	-1.13	12.15	0.27	4.75	51.79
Bond Term	2.42	7.72	0.04	1.48	14.78
Bond Default	2.25	7.16	-1.35	14.2	33.2
PTFSBD	-28.37	51.86	1.44	2.89	99.87
PTFSFX	-20.93	67.24	1.41	2.92	98.23
PTFSCOM	-0.08	0.48	1.27	2.63	2.07
PTFSIR	-3.34	98.32	4.13	23.77	99.22
PTFSSTK	-52.34	44	0.98	1.99	100
GSCI ex Rf	1.62	22.61	-0.37	1.45	67.91

Table 2.5: **Risk Factors Correlation**

Table 2.5 contains correlations of the Fung-Hsieh factors for the period January 1993 to December 2010.

Correlation	**Equity Size**	**Bond Term**	**Bond Default**	**PTFSBD**	**PTFSFX**	**PTFSCOM**	**PTFSIR**	**PTFSSTK**	**GSCI**
Equity Market	0.04	-0.15	0.42	-0.2	-0.19	-0.13	-0.27	-0.19	0.22
Equity Size		-0.16	0.2	-0.09	0	-0.03	-0.1	-0.09	0.16
Bond Term			-0.27	0.2	0.14	0.1	0.09	0.19	-0.06
Bond Default				-0.14	-0.27	-0.19	-0.42	-0.29	0.25
Trend Bond					0.23	0.18	0.2	0.15	-0.05
Trend Currency						0.38	0.3	0.22	-0.06
Trend Commodity							0.3	0.09	0.05
Trend Interest Rates								0.3	-0.29
Trend Stock									-0.14
GSCI ex Rf									

Table 2.6: **CTA Average Performance**

Table 2.6 reports average performance of CTAs for the BarclayHedge database for the period January 1994 to December 2010. Panel A represents average performance for equally-weighted portfolios and Panel B for value-weighted portfolios. Panel C shows performance of indices. Panel D shows results of both equally-weighted portfolios as well as value-weighted portfolios adjusted for backfilling bias of 12 months. Panel E shows the results of equal-weighted performance in size groups. Funds are sorted into size groups every month based on the monthly AUM data.

Panel A: Equally-Weighted Portfolios

CTA Average Performance January 1994-2010 -EW

	No. of funds	Mean Rtn (%)	Stdv	t(mean=0)	Median	Min	Max	Mean Ann.	Stdv Ann.	Sharpe
Aggregate EW Index	1938	0.65	1.97	4.85	0.47	-3.84	6.33	7.82	6.81	1.15
Systematic EW Index	1251	0.60	2.56	3.44	0.54	-5.24	7.73	7.08	8.85	0.80
Systematic S-T	232	0.66	1.37	7.08	0.59	-3.46	4.91	8.04	4.75	1.69
Systematic M-T	667	0.64	2.94	3.20	0.40	-5.4	9.69	7.35	10.19	0.72
Systematic L-T	156	0.79	4.50	2.58	0.44	-9.78	14.49	8.56	15.57	0.55
Systematic Counter Trend	22	0.48	2.47	2.86	0.37	-8.10	9.7	5.50	8.56	0.64
Systematic Pattern Recognition	70	0.67	2.02	4.87	0.48	-4.26	5.55	8.12	7.00	1.16
Systematic Spread/RV	104	0.42	1.45	4.26	0.32	-3.7	4.73	5.08	5.01	1.01
Discretionary EW Index	578	0.72	1.22	8.67	0.54	-2.06	7.61	8.90	4.23	2.10
Discretionary Fund	121	0.60	2.10	4.20	0.12	-3.87	12.16	7.17	7.28	0.98
Discretionary Fund & Tech	184	0.95	1.81	7.71	0.69	-3.17	10.95	11.81	6.26	1.89
Discretionary Tech	214	0.79	1.64	7.08	0.60	-2.79	5.56	9.76	5.67	1.72
Discretionary Spread/RV	49	0.58	1.60	5.33	0.37	-5.98	7.11	7.07	5.54	1.28
Options EW Index	109	0.92	2.61	5.18	1.50	-13.93	9.81	11.16	9.06	1.23

Panel B: Value-Weighted Portfolios

CTA Average Performance January 1994-2010 -VW

	No. of funds	Mean Rtn (%)	Stdv	t(mean=0)	Median	Min	Max	Mean Ann.	Stdv Ann.	Sharpe
Aggregate VW Index	1938	0.63	2.68	3.45	0.48	-4.7	9.01	7.31	9.29	0.79
Systematic VW Index	1251	0.67	3.02	3.26	0.43	-5.68	10.02	7.80	10.46	0.75
Systematic S-T	232	0.86	1.95	6.48	0.66	-3.23	15.55	10.61	6.77	1.57
Systematic M-T	667	0.9	3.83	3.45	0.52	-7.62	12.95	10.9	13.25	0.82
Systematic L-T	156	0.67	4.4	2.24	0.66	-12.77	16.18	7.05	15.23	0.46
Systematic Counter Trend	22	0.15	2.81	0.78	0.06	-10.58	11.04	1.33	9.74	0.14
Systematic Pattern Recognition	70	0.51	2.53	2.96	0.24	-7.94	6.79	5.84	8.78	0.67
Systematic Spread/RV	104	0.48	2.02	3.49	0.52	-5.56	5.18	5.67	7.00	0.81
Discretionary VW Index	578	0.39	1.47	3.90	0.20	-4.31	6.57	4.68	5.08	0.92
Discretionary Fund	121	0.34	1.64	3.05	0.22	-6.37	10.2	3.95	5.70	0.69
Discretionary Fund & Tech	184	0.55	2.58	3.13	0.51	-8.51	8.51	6.43	8.94	0.72
Discretionary Tech	214	0.40	1.96	3.00	0.19	-6.00	8.36	4.61	6.78	0.68
Discretionary Spread/RV	49	0.28	1.86	2.21	0.32	-6.78	9.13	3.26	6.46	0.50
Options VW Index	109	0.41	2.04	2.95	0.57	-9.75	7.24	4.77	7.06	0.68

Panel C: Passive Strategies	Mean Rtn (%)	Stdv	t(mean=0)	Median	Min	Max	Mean Ann.	Stdv Ann.	Sharpe
Equity									
S&P 500	0.75	4.54	2.43	1.32	-16.8	9.78	8.04	15.71	0.26
MSCI World ex US	0.41	4.85	1.24	0.68	-20.87	12.39	3.58	16.8	0.00
Market proxy-Rf	0.51	4.71	1.59	1.27	-18.54	11.04	4.87	16.31	0.30
F&F SMB factor	0.03	3.68	0.12	-0.1	-22.06	13.74	-0.49	12.73	-0.36
F&F HML factor	0.4	3.48	1.69	0.34	-9.93	13.88	4.18	12.07	-0.01
Momentum	0.48	5.65	1.25	0.71	-34.75	18.4	3.72	19.56	0.04
Bond									
Barclays Aggregate Bond Index	0.51	1.10	6.81	0.61	-3.36	3.87	6.18	3.83	0.31
Barclays Municipal 10 Year Index	0.45	1.37	4.83	0.60	-4.20	4.70	5.43	4.74	0.11
Citi 5 Year Treasury Benchmark	0.47	1.34	5.15	0.49	-3.57	4.65	5.66	4.65	0.16
Barclays Mortgage Backed Securities Index	0.52	0.86	8.89	0.58	-2.6	3.93	6.34	2.98	0.44
Commodity									
GSCI	0.64	6.52	1.44	0.77	-28.2	19.67	5.17	22.6	0.12
Alternative Investments									
Barclay CTA Index	0.52	2.20	3.47	0.36	-4.7	6.45	6.11	7.62	0.18
Dow Jones Credit Suisse Hedge Fund Index	0.78	2.22	5.16	0.82	-7.55	8.53	9.42	7.70	0.58
Dow Jones Credit Suisse Managed Futures Index	0.59	3.41	2.54	0.4	-9.35	9.95	6.63	11.8	0.19
HFRX Absolute Return Index	0.31	1.10	4.14	0.46	-4.39	2.31	3.68	3.81	-0.31

Table 2.6 Continued: CTA Average Performance Bias Adjusted

Table 2.6 Panel D shows results of both equally-weighted and value-weighted portfolios adjusted for backfilling bias of 12 months. Every month funds are sorted into size groups based on the monthly AUM data.

Panel D: Bias adjusted CTA Average Performance 1994-2010										
Equally-Weighted Portfolios	**No. of funds**	**Mean return**	**Stdv**	**t(mean=0)**	**Median**	**Min**	**Max**	**Mean Ann.**	**Stdv Ann.**	**Sharpe**
Aggregate EW Index	**1527**	**0.55**	**2.09**	**3.87**	**0.37**	**-4.35**	**6.69**	**6.51**	**7.25**	**0.90**
Systematic EW Index	**1010**	**0.53**	**2.68**	**2.91**	**0.36**	**-5.75**	**8.35**	**6.13**	**9.27**	**0.66**
Systematic S-T	181	0.50	1.37	5.36	0.45	-3.77	4.94	5.99	4.76	1.26
Systematic M-T	542	0.53	3.04	2.56	0.29	-5.9	10.31	5.99	10.55	0.57
Systematic L-T	138	0.71	4.62	2.26	0.12	-9.84	13.39	7.50	16.01	0.47
Systematic Counter Trend	11	0.31	2.71	1.68	0.32	-12.61	8.67	3.27	9.39	0.35
Systematic Pattern Recognition	61	0.56	2.21	3.72	0.44	-4.77	5.86	6.57	7.65	0.86
Systematic Spread/RV	77	0.24	1.40	2.52	0.21	-3.84	4.66	2.79	4.86	0.57
Discretionary EW Index	**437**	**0.56**	**1.25**	**6.58**	**0.38**	**-2.22**	**5.68**	**6.9**	**4.32**	**1.60**
Discretionary Fund	99	0.41	1.90	3.17	0.16	-4.08	9.93	4.76	6.57	0.72
Discretionary Fund & Tech	138	0.69	1.93	5.25	0.67	-3.51	8.3	8.34	6.67	1.25
Discretionary Tech	156	0.64	1.84	5.11	0.23	-2.53	7.21	7.72	6.36	1.21
Discretionary Spread/RV	37	0.36	1.22	4.34	0.41	-3.29	6.83	4.31	4.23	1.02
Options EW Index	**84**	**0.75**	**2.77**	**3.98**	**1.07**	**-14.88**	**7.83**	**8.91**	**9.61**	**0.93**
Value-Weighted Portfolios	**No. of funds**	**Mean return**	**Stdv**	**t(mean=0)**	**Median**	**Min**	**Max**	**Mean Ann.**	**Stdv Ann.**	**Sharpe**
Aggregate VW Index	**1527**	**0.62**	**2.71**	**3.36**	**0.48**	**-4.95**	**9.05**	**7.30**	**9.38**	**0.78**
Systematic VW Index	**1010**	**0.68**	**3.05**	**3.28**	**0.44**	**-6.01**	**10.25**	**7.88**	**9.43**	**0.84**
Systematic S-T	181	0.83	2.00	6.10	0.69	-3.29	17.58	10.17	6.93	1.47
Systematic M-T	542	0.72	3.88	2.73	0.54	-7.71	12.98	7.99	13.46	0.59
Systematic L-T	138	0.62	4.46	2.04	0.66	-12.81	16.22	6.39	15.46	0.41
Systematic Counter Trend	11	0.1	3.07	0.48	0.09	-12.61	11.16	0.68	10.63	0.06
Systematic Pattern Recognition	61	0.42	2.61	2.37	0.17	-8.06	7.86	4.79	9.05	0.53
Systematic Spread/RV	77	0.49	2.08	3.46	0.54	-5.67	5.18	5.73	7.21	0.79
Discretionary VW Index	**437**	**0.36**	**1.52**	**3.48**	**0.18**	**-4.66**	**6.8**	**4.26**	**5.25**	**0.81**
Discretionary Fund	99	0.29	1.72	2.48	0.18	-7.1	10.75	3.31	5.95	0.56
Discretionary Fund & Tech	138	0.42	2.68	2.30	0.47	-8.58	8.71	4.69	9.30	0.50
Discretionary Tech	156	0.41	2.04	2.95	0.21	-5.7	8.75	4.72	7.07	0.67
Discretionary Spread/RV	37	0.27	1.81	2.19	0.29	-5.39	10.18	3.14	6.26	0.50
Options VW Index	**84**	**0.40**	**2.25**	**2.61**	**0.56**	**-9.77**	**8.16**	**4.65**	**7.81**	**0.60**

Table 2.6 Continued: CTA Equally-Weighted Performance Bias Adjusted in Size Groups

Table 2.6 Panel E shows the results of equal-weighted performance in size groups. Every month funds are sorted into size groups based on the monthly AUM data.

Panel E: Performance in Size Groups: Equally-Weighted Portfolios January 1994-December 2010										
All CTAs	**No. of funds**	**Mean return**	**Stdv**	**t(mean=0)**	**Median**	**Min**	**Max**	**Mean Ann.**	**Stdv Ann.**	**Sharpe**
AUM $\leq$ US$10 million	1120	0.62	2.04	4.34	0.41	-4.04	6.53	7.40	7.07	1.05
$\leq$ US$10 million AUM & $\leq$ 50 million	736	0.48	2.27	3.02	0.33	-4.57	7.79	5.59	7.86	0.71
$\leq$ US$50 million AUM & $\leq$ 250 million	474	0.42	2.34	2.56	0.27	-5.5	7.73	4.78	8.1	0.59
$\geq$ US$250 million AUM	190	0.48	2.62	2.62	0.26	-6.73	9.09	5.47	9.07	0.60
SYSTEMATIC	**No. of funds**	**Mean return**	**Stdv**	**t(mean=0)**	**Median**	**Min**	**Max**	**Mean Ann.**	**Stdv Ann.**	**Sharpe**
AUM $\leq$ US$10 million	730	0.58	2.61	3.17	0.38	-5.41	8.04	6.17	10.31	0.74
$\leq$ US$10 million AUM & $\leq$ 50 million	499	0.49	2.86	2.45	0.17	-5.94	9.05	5.53	9.92	0.56
$\leq$ US$50 million AUM &$\leq$ 250 million	327	0.45	2.95	2.18	0.30	-7.01	9.26	4.43	10.2	0.49
$\geq$ US$250 million AUM	144	0.56	2.97	2.69	0.28	-7.35	9.97	6.73	9.04	0.60
DISCRETIONARY	**No. of funds**	**Mean return**	**Stdv**	**t(mean=0)**	**Median**	**Min**	**Max**	**Mean Ann.**	**Stdv Ann.**	**Sharpe**
AUM $\leq$ US$10 million	319	0.66	1.44	6.55	0.48	-2.63	7.91	8.14	4.99	1.63
$\leq$ US$10 million AUM & $\leq$ 50 million	207	0.45	1.28	5.02	0.24	-2.75	6.88	5.42	4.45	1.22
$\leq$ US$50 million AUM & $\leq$ 250 million	131	0.34	1.14	4.26	0.27	-2.47	5.22	4.09	3.94	1.04
$\geq$ US$250 million AUM	39	0.42	2.37	2.53	0.20	-6.66	8.94	4.85	8.2	0.59

Table 2.7: **Instant History Bias Effect on Value and Equally-Weighted Portfolios**

Table 2.7 shows the effect of various screens for instant history bias on value and equally-weighted portfolios.

Backfill Bias and CTA Performance				
Summary of the effect of bias on returns				
	Mean	**Stdv**	**Mean Ann.**	**Stdv Ann.**
Aggregate EW no backfill removed	0.65	1.97	7.82	6.81
Aggregate VW no bias removed	0.63	2.68	7.31	9.29
Aggregate EW 12 month bias removed	0.55	2.09	6.51	7.25
Aggregate VW 12 months bias removed	0.62	2.71	7.30	9.38
Aggregate EW 24 month bias removed	0.54	2.22	6.35	7.69
Aggregate VW 24 months bias removed	0.68	2.79	7.98	9.65
Aggregate EW with 43 months bias removed	0.50	2.33	5.77	8.08
Aggregate VW with 43 months bias removed	0.72	2.87	8.51	9.94

Table 2.8: **Return Decomposition of EW CTA Index (with AUM filter)**

Table 2.8 Panel A reports the results of regressing an equally-weighted index of excess CTA returns (with AUM filter) on the Fung and Hsieh (2004) seven-factor model extended with PTFSIR (the excess return of the portfolio of lookback straddle options on interest rate), PTFSSTK (the excess return of the portfolio of lookback straddle options on stock) and GSCIRF (the excess return on the GSCI index). Column two shows the results of the regression for the entire period, January 1994 to December 2010. Columns three to six report the results of the regression (4.6) for each subperiod. D_1 is set to one during the first period (January 1994 to September 1998) and zero elsewhere, D_2 is set to one during the second period (October 1998 to March 2003) and zero elsewhere, D_3 is set to one during the third period (April 2003 to July 2007) and zero elsewhere and D_4 is set to one during the final period (August 2007 to end of data, December 2010) and zero elsewhere. Values of the t-statistics, calculated using Newey-West (1987) heteroskedasticity and autocorrelation consistent estimates of the standard errors, are reported in italics below each coefficient. Statistical significance at the 1%, 5% and 10% levels is denoted by ***, ** and *, respectively. The bottom panel reports the Chi-squared statistics for the Chow test for structural breaks.

Panel A:

Factors	**Jan 1994-Dec 2010**	**Period I**	**Period II**	**Period III**	**Period IV**
Constant	**0.006*****	**0.005****	0.002	0.001	**0.015*****
	4.345	1.907	0.720	0.381	6.940
SNPMRF	0.001	0.047	-0.060	**0.474*****	0.005
	0.031	0.625	-1.131	7.169	0.112
SCMLC	0.013	**-0.140****	0.051	0.069	-0.132
	0.322	-1.857	0.777	1.044	-1.559
BD10RET	**0.168****	0.102	**0.383*****	**0.256*****	**-0.187*****
	2.651	0.698	2.635	3.175	-2.623
BAAMTSY	0.045	0.026	0.182	-0.190	**-0.084*****
	0.660	0.076	0.858	-0.993	-2.157
PTFSBD	**0.027*****	**0.038*****	**0.033*****	0.031	**0.056*****
	3.330	2.457	2.047	1.526	4.162
PTFSFX	**0.042*****	**0.034*****	**0.085*****	**0.030*****	-0.017
	5.546	**3.871**	6.282	3.534	-1.595
PTFSCOM	**0.037****	**0.092*****	-0.026**	0.017**	**0.089*****
	2.796	5.396	-1.719	1.739	5.270
PTFSIR	-0.008*	-0.012	**0.025*****	0.010	**-0.022*****
	-1.833	-1.028	3.345	0.908	-6.320
PTFSSTK	**0.030*****	0.015	0.020	0.021	**0.068*****
	2.952	0.743	1.124	1.729	5.047
GSCIRF	**0.0742*****	0.081**	**0.088*****	**0.074*****	0.055**
	3.600	1.698	2.116	2.918	1.754
Adjusted R^2	0.3822	0.5224			
No of months	204	204			
Chow Test for Structural Breaks					
Sep-98	χ^2 (10)				49.78***
Mar-00	χ^2 (10)				27.86
Mar-03	χ^2 (10)				47.81***
Nov-07	χ^2 (10)				77.26***

Table 2.8 Continued: Return Decomposition of Value-Weighted CTA Index (with AUM filter)

Table 2.8 Panel B reports the results of regressing a value-weighted index of excess CTA returns on the Fung and Hsieh (2004) seven-factor model extended with PTFSIR (the excess return of the portfolio of lookback straddle options on interest rate), PTFSSTK (the excess return of the portfolio of lookback straddle options on stock) and GSCIRF (the excess return on the GSCI index). Column two shows the results of the regression for the entire period, January 1994 to December 2010. Columns three to six report the results of the regression (4.6) for each subperiod. D_1 is set to one during the first period (January 1994 to September 1998) and zero elsewhere, D_2 is set to one during the second period (October 1998 to March 2003) and zero elsewhere, D_3 is set to one during the third period (April 2003 to July 2007) and zero elsewhere and D_4 is set to one during the final period (August 2007 to end of data, December 2010) and zero elsewhere. Values of the t-statistics, calculated using Newey-West (1987) heteroskedasticity and autocorrelation consistent estimates of the standard errors, are reported in italics below each coefficient. Statistical significance at the 1%, 5% and 10% levels is denoted by ***, ** and *, respectively. The bottom panel reports the Chi-squared statistics for the Chow test for structural breaks.

Panel B:

	Jan 1994-Dec 2010	**Period I**	**Period II**	**Period III**	**Period IV**
Constant	**0.0088*** **	**0.0054** **	0.0064*	0.0041	**0.0179*** **
	-5.2163	2.2991	1.9117	1.3047	5.5078
SNPMRF	-0.0132	0.0197	-0.1139*	**0.6163*** **	0.0270
	-0.2968	*0.2502*	*1.9117*	*7.0329*	*0.4251*
SCMLC	-0.0005	**-0.1735** **	0.0417	0.0505	-0.2089
	-0.0092	-2.2899	0.5770	0.5720	-1.5391
BD10RET	**0.2389*** **	0.1987	0.3787**	**0.3088*** **	-0.0756
	3.1257	*1.3620*	*2.3670*	*3.3045*	*-0.6409*
BAAMTSY	0.0263	-0.0561	0.1569	-0.0268	**-0.1398** **
	0.3069	*-0.1707*	*0.6554*	*-0.1201*	*-1.7416*
PTFSBD	**0.0294*** **	**0.0398** **	0.0321	0.0422**	**0.060*** **
	3.091	*2.4657*	*1.8155*	*1.7054*	*2.7590*
PTFSFX	**0.0397*** **	**0.0289*** **	**0.0793*** **	**0.0330*** **	**-0.033** **
	4.4581	*3.3939*	*5.5056*	*2.6583*	*-1.7781*
PTFSCOM	**0.0363** **	**0.0966*** **	-0.0305*	0.0056	**0.1030*** **
	2.5534	*6.5198*	*-1.7886*	*0.4475*	*4.0371*
PTFSIR	**-0.0129** **	-0.0182	**0.0412*** **	**0.0353*** **	**-0.0306*** **
	-2.0199	-1.5235	*4.2641*	2.2095	-4.3351
PTFSSTK	**0.0427*** **	0.0212	0.0262	**0.0412*** **	**0.0786*** **
	3.2056	*1.0028*	*1.2536*	*2.5563*	*4.0091*
GSCIRF	**0.0659** **	0.0830	0.0969*	0.0487**	0.0414
	2.4503	*1.6640*	*1.7934*	*1.6818*	*0.8578*
Adjusted R^2	0.3209	0.4987			
No. of months	204	204			
Chow Test for Structural Breaks					
Sep-98	χ^2 (10)				49.15***
Mar-00	χ^2 (10)				20.57*
Mar-03	χ^2 (10)				60.17***
Nov-07	χ^2 (10)				68.10***

Table 2.9: **Average Performance of the CTAs by Investment Objective, (Equally-Weighted with AUM filter)**

Table 2.9 reports the results of regressing an equally-weighted index of excess CTA returns for each investment objective on the Fung and Hsieh (2004) seven-factor model extended with PTFSIR (the excess return of the portfolio of lookback straddle options on interest rate), PTFSSTK (the excess return of the portfolio of lookback straddle options on stock) and GSCIRF (the excess return on the GSCI index). Panel A reports the results for the entire period whilst Panel B shows the results for the subperiods. Column two of Panel A shows the number of funds used to construct the index after adjusting for instant history and survivorship bias and taking funds with at least 24 months of returns. Column three reports the alpha of the model for the entire period, January 1994 to December 2010, with Newey-West (1987) t-statistics in parentheses. Alphas are annualized. Column four shows the adjusted R^2 of the regression. Columns three to six of Panel B report alphas for the subperiods and column seven shows the adjusted R^2 for the model with breaks. Statistical significance at the 1%, 5% and 10% levels is denoted by ***, ** and *, respectively.

Strategy	No. of funds	Alpha (%) Entire Period	Adjusted R^2				
Panel A:							
SYSTEMATIC	1010	0.73*** (4.184)	0.385				
Short-Term	181	0.39*** (3.018)	0.224				
Medium-Term	542	0.83*** (4.174)	0.396				
Long-Term	138	0.10*** (3.566)	0.341				
Spread/RV	77	0.27** (2.057)	0.117				
Pattern Rec	61	0.91*** (3.492)	0.266	**Panel C:**			
				Alpha (%) Period I	Alpha (%) Period II	Alpha (%) Period III	Adjusted R^2
DISCRETIONARY	437	0.38*** (4.314)	0.239	0.09 (0.5344)	0.36*** (2.686)	0.87*** (5.306)	0.28
Fundamental & Technical	138	0.60*** (3.301)	0.121	0.32 (0.896)	0.65** (2.742)	0.62*** (3.190)	0.123
Fundamental	99	0.23* (1.90)	0.176	-0.14 (-0.784)	0.13 (0.746)	0.14*** (3.899)	0.281
Technical	156	0.38*** (3.457)	0.248	0.13 (0.831)	0.39** (2.560)	0.56** (2.679)	0.373
OPTIONS	84	0.00 (-0.028)	0.296				
Panel B:							
Strategy	No. of funds	Alpha (%) Period I	Alpha (%) Period II	Alpha (%) Period III	Alpha (%) Period IV	Adjusted R^2	
SYSTEMATIC	1010	0.6*** (2.29)	0.71** (1.94)	0.44 (1.28)	0.18*** (5.50)	0.512	
Short-Term	181	0.12*** (2.82)	0.13*** (3.85)	0.43*** (4.024)	0.39** (2.682)	0.304	
Medium-Term	542	0.64*** (2.06)	0.01*** (2.15)	0.62 (1.23)	0.28*** (5.20)	0.534	
Long-Term	138	0.63*** (2.031)	0.32 (0.307)	-0.01* (-0.18)	0.62** (1.79)	0.493	
Spread/RV	77	0.33*** (2.04)	-0.6*** (-2.09)	0.48*** (2.37)	0.14*** (3.47)	0.307	
Pattern Rec	61	0.96*** (2.98)	0.42 (1.14)	0.19 (0.59)	0.14*** (3.31)	0.319	
DISCRETIONARY	437	0.20 (1.16)	0.01 (0.67)	0.01 (1.30)	0.12*** (3.08)	0.293	
Fundamental & Technical	138	0.54 (1.14)	-0.24*(-0.74)	0.38** (1.91)	0.12*** (2.46)	0.149	
Fundamental	99	0 (0.08)	-0.47* (-0.21)	0.29*** (2.13)	0.15*** (3.90)	0.235	
Technical	156	0.26 (1.26)	0.73*** (3.17)	-0.01*(0.24)	0.56*** (3.40)	0.465	
OPTIONS	84	-0.08*(-0.319)	-0.26 (-0.749)	0 (0.030)	-0.25*(-0.587)	0.405	

Table 2.10: **Quantitative Measures and Transition Probabilities of Have-Alpha and Beta-Only Funds, Systematic and Discretionary CTAs respectively**

Table 2.10 Panel A and Panel B report quantitative measures and transition probabilities of have-alpha and beta-only funds for the period January 1993 to December 2010. The top part of the tables reports results from the classification period. The rows show the two year periods in which CTAs are classified into alpha and beta funds. The second column shows the total number of funds in each period. Columns three and four show the proportion of have-alpha and beta-only funds. Columns five, six and seven show the annual average level of alpha, the average t-statistics of alpha and average AUM of have-alpha funds. Columns eight, nine and ten report the same information for the beta-only funds. The second part of the table, shows the percentage of have-alpha and beta-only funds that are classified in the subsequent non-overlapping periods as have-alpha, beta-only, liquidated, stopped reporting or real failures. Columns five, six and seven report level of alpha, average t-statistics and AUM for funds alpha funds that were subsequently reclassified as have-alpha funds.

Panel A: SYSTEMATIC		Proportion							
Classification Period	**No. of funds**	**Have-Alpha**	**Beta-Only**	**alpha of a funds**	**t-stat**	**AUM a**	**alpha beta funds**	**t-stat**	**AUM of beta funds**
1994-1995	94	0.60	0.40	0.31	3.21	113.58	0.03	-0.05	121.45
1995-1996	91	0.30	0.70	0.16	2.47	129.60	-0.05	-0.67	116.33
1996-1997	101	0.15	0.85	0.18	3.35	170.09	-0.05	-0.80	112.61
1997-1998	116	0.17	0.83	0.20	3.16	207.06	-0.04	-0.78	140.29
1998-1999	120	0.24	0.76	0.24	3.13	285.89	0.00	-0.10	178.83
1999-2000	125	0.22	0.78	0.33	2.37	248.84	0.02	-0.11	214.22
2000-2001	127	0.25	0.75	0.20	2.71	372.76	-0.04	-0.68	228.10
2001-2002	122	0.25	0.75	0.18	3.03	423.80	0.01	0.05	277.83
2002-2003	127	0.42	0.58	0.20	2.66	711.98	0.01	0.16	172.68
2003-2004	144	0.24	0.76	0.15	2.66	999.78	-0.07	-0.72	438.76
2004-2005	143	0.39	0.61	0.23	3.37	1197.30	-0.06	-0.65	636.04
2005-2006	142	0.34	0.66	0.24	3.26	892.37	0.01	-0.04	887.50
2006-2007	157	0.39	0.61	0.18	2.58	1033	0.01	-0.14	1053.79
2007-2008	168	0.39	0.61	0.16	2.23	1670.99	0.04	0.28	945.39
2007-2009	184	0.49	0.51	0.26	3.26	354.29	0.03	0.25	2008.97
2009-2010	180	0.49	0.51	0.26	3.30	362.41	0.03	0.29	2030.05
All cases	**134**	**0.33**	**0.67**	**0.22**	**2.92**	**573.39**	**-0.01**	**-0.23**	**597.68**
P(2-Year Transition)	**From/To**	**Have-Alpha**	**Beta**	**Level of alpha**	**t-stat**	**AUM**	**Liquidated**	**Stopped Reporting**	**Failure**
1996-1997	Have-Alpha	0.07	0.75	0.27	3.15	178.35	0.71	0.20	0.50
	Beta-Only	0.16	0.55	0.19	2.69	208.53	1.00	0.00	0.64
1997-1998	Have-Alpha	0.22	0.70	0.15	1.73	271.43	0.75	0.25	0.30
	Beta-Only	0.09	0.67	0.20	1.94	60.47	1.00	0.00	0.50
1998-1999	Have-Alpha	0.07	0.73	0.18	3.36	1195.83	0.71	0.29	0.36
	Beta-Only	0.16	0.60	0.09	0.87	127.21	0.92	0.08	0.44
1999-2000	Have-Alpha	0.40	0.55	-0.03	0.16	658.17	0.71	0.29	0.36
	Beta-Only	0.11	0.66	-0.02	-0.26	94.80	0.92	0.08	0.51
2000-2001	Have-Alpha	0.17	0.79	0.17	2.74	455.06	0.73	0.27	0.33
	Beta-Only	0.09	0.67	0.17	1.67	454.44	0.92	0.08	0.48
2001-2002	Have-Alpha	0.41	0.48	0.19	2.18	349.14	0.78	0.22	0.39
	Beta-Only	0.15	0.69	0.06	0.54	359.66	0.93	0.07	0.51
2002-2003	Have-Alpha	0.35	0.53	0.08	1.05	112.71	0.75	0.25	0.35
	Beta-Only	0.34	0.51	0.15	1.23	776.88	0.91	0.09	0.48
2003-2004	Have-Alpha	0.30	0.63	0.08	1.53	2307.97	0.70	0.25	0.31
	Beta-Only	0.17	0.67	0.09	1.37	940.14	0.92	0.08	0.49
2004-2005	Have-Alpha	0.19	0.74	0.01	0.07	2680.50	0.75	0.25	0.35
	Beta-Only	0.15	0.66	0.03	0.42	406.89	0.92	0.08	0.50
2005-2006	Have-Alpha	0.24	0.59	0.17	2.07	3556.48	0.77	0.23	0.41
	Beta-Only	0.30	0.47	0.17	1.93	385.03	0.90	0.10	0.49
2006-2007	Have-Alpha	0.52	0.33	0.18	2.90	2858.33	0.74	0.22	0.39
	Beta-Only	0.28	0.53	0.47	4.10	568.57	0.90	0.10	0.51
2007-2008	Have-Alpha	0.38	0.58	0.19	2.19	2981.37	0.80	0.20	0.43
	Beta-Only	0.33	0.49	0.17	2.19	1626.60	0.90	0.10	0.53
2008-2009	Have-Alpha	0.48	0.39	0.09	1.40	597.69	0.71	0.22	0.44
	Beta-Only	0.34	0.42	0.08	0.92	271.57	0.87	0.13	0.52
2009-2010	Have-Alpha	0.36	0.44	0.02	0.51	1946.93	0.72	0.18	0.40
	Beta-Only	0.29	0.43	0.04	0.67	2451.09	0.80	0.13	0.48
All cases	**Have-Alpha**	**0.30**	**0.59**	**0.12**	**1.79**	**1439.28**	**0.74**	**0.24**	**0.38**
	Beta-Only	**0.21**	**0.58**	**0.14**	**1.51**	**483.14**	**0.92**	**0.08**	**0.51**
	Wald Statistic	37.82***	2.82				24.15***	92.03***	67.94***

Panel B: DISCRETIONARY

Classification Period Period	No. of funds	Have-Alpha	Beta-Only	a of alpha funds	t-stat	AUM of alpha funds	a of beta funds	t-stat	AUM of beta funds
1994-1995	45	0.27	0.73	0.19	2.92	68.04	-0.01	-0.51	84.97
1995-1996	49	0.33	0.67	0.10	5.10	51.60	-0.02	-0.59	75.45
1996-1997	40	0.32	0.68	0.11	5.49	96.94	0.00	-0.64	85.48
1997-1998	43	0.35	0.65	0.16	3.90	89.38	-0.06	-0.95	123.09
1998-1999	46	0.20	0.80	0.15	5.99	105.68	-0.04	-1.10	97.36
1999-2000	35	0.29	0.71	0.21	2.97	105.35	-0.01	-1.15	105.43
2000-2001	37	0.30	0.70	0.22	2.44	113.80	-0.02	-0.20	75.34
2001-2002	35	0.40	0.60	0.20	2.71	112.63	-0.05	-0.76	79.55
2002-2003	34	0.29	0.71	0.09	2.86	232.58	-0.03	-0.54	85.91
2003-2004	36	0.19	0.81	0.09	2.56	243.70	0.02	0.29	232.88
2004-2005	42	0.24	0.76	0.19	2.52	182.50	0.01	-0.14	312.07
2005-2006	45	0.22	0.78	0.01	2.53	334.05	0.00	-1.18	169.32
2006-2007	44	0.25	0.75	0.24	2.74	370.03	-0.01	-2.47	222.33
2007-2008	44	0.20	0.80	0.19	2.53	200.10	0.02	-0.77	328.54
2007-2009	49	0.29	0.57	0.19	2.85	314.55	-0.28	-0.32	178.28
2009-2010	52	0.48	0.52	0.17	2.97	270.05	0.05	-0.27	178.51
All cases	**42.25**	**0.29**	**0.71**	**0.16**	**3.32**	**180.68**	**-0.03**	**-0.71**	**152.16**
P(2-Year Transition)	**From/To**	**Have-Alpha**	**Beta**	**Level of alpha**	**t-stat**	**AUM**	**Liquidated**	**Stopped Reporting**	**Failure**
1996-1997	Have-Alpha	0.58	0.17	0.19	4.28	90.67	1.00	0.00	0.67
	Beta-Only	0.12	0.52	0.09	2.47	26.02	0.92	0.08	0.67
1997-1998	Have-Alpha	0.25	0.56	0.07	7.90	93.70	1.00	0.00	0.40
	Beta-Only	0.30	0.36	0.14	1.21	72.04	0.85	0.15	0.65
1998-1999	Have-Alpha	0.29	0.43	0.06	9.28	167.11	0.88	0.13	0.38
	Beta-Only	0.08	0.73	0.28	2.95	79.27	0.86	0.14	0.64
1999-2000	Have-Alpha	0.40	0.40	0.04	1.38	108.97	0.82	0.18	0.45
	Beta-Only	0.14	0.39	-0.06	1.07	94.12	0.85	0.15	0.58
2000-2001	Have-Alpha	0.33	0.44	0.04	4.20	176.68	0.83	0.17	0.50
	Beta-Only	0.08	0.43	0.08	2.05	131.41	0.86	0.14	0.60
2001-2002	Have-Alpha	0.27	0.27	0.21	1.93	284.37	0.81	0.19	0.44
	Beta-Only	0.21	0.42	0.07	1.73	67.95	0.86	0.14	0.59
2002-2003	Have-Alpha	0.27	0.27	0.09	1.75	273.14	0.84	0.16	0.42
	Beta-Only	0.15	0.69	0.25	2.62	303.91	0.85	0.15	0.58
2003-2004	Have-Alpha	0.14	0.71	0.05	3.04	70.73	0.85	0.15	0.45
	Beta-Only	0.14	0.67	0.17	2.23	54.14	0.86	0.14	0.59
2004-2005	Have-Alpha	0.22	0.67	0.02	0.96	538.48	0.86	0.14	0.43
	Beta-Only	0.24	0.56	0.21	1.90	89.51	0.87	0.13	0.57
2005-2006	Have-Alpha	0.22	0.67	0.00	0.17	211.36	0.82	0.18	0.45
	Beta-Only	0.15	0.59	0.30	3.74	685.67	0.85	0.15	0.56
2006-2007	Have-Alpha	0.36	0.36	0.26	2.51	520.28	0.76	0.24	0.48
	Beta-Only	0.06	0.45	0.13	1.85	132.54	0.86	0.14	0.60
2007-2008	Have-Alpha	0.20	0.60	0.30	2.40	289.59	0.74	0.26	0.48
	Beta-Only	0.11	0.51	0.14	1.96	206.91	0.85	0.15	0.58
2008-2009	Have-Alpha	0.60	0.20	0.13	1.58	849.44	0.69	0.31	0.48
	Beta-Only	0.29	0.38	0.04	2.13	98.73	0.84	0.16	0.57
2009-2010	Have-Alpha	0.11	0.56	0.01	3.16	178.66	0.67	0.30	0.47
	Beta-Only	0.31	0.40	0.11	2.48	618.99	0.79	0.15	0.54
All cases	**Have-Alpha**	**0.30**	**0.45**	**0.10**	**3.18**	**275.23**	**0.83**	**0.17**	**0.46**
	Beta-Only	**0.17**	**0.51**	**0.14**	**2.17**	**190.09**	**0.86**	**0.14**	**0.59**
	Wald Statistic	45.89***	2.56				2.03	2.89*	28.56****

Table 2.11: **Results of Performance Persistence for all CTAs**

Table 2.11 reports the out-of-sample performance of sorting CTAs into decile portfolios on the basis of two separate variables: on OLS alpha from the ten factor model used in this study and on the t-statistics of alpha. Portfolios are re-balanced annually. Reported results are for the sample period January 1994 to December 2010. Both alpha and t-statistics of alpha are measured using the most recent 24 months of data preceding the evaluation period. Portfolios are equally-weighted and weights are readjusted whenever a fund disappears from the sample. For each decile, the table shows annualized alpha, t-statistics of alpha and respective p-value, the adjusted-R^2 from an OLS regression of portfolio return on the 10-factor model used in this study and annulled return in percentages. The table also shows the information ratio (IR), the tracking error, and the coefficients of the ten factors. Decile 1 comprises funds with the highest OLS alphas (t-statistics) and Decile 10 contains funds with the lowest alpha. The last row shows the spread calculated as the difference between the top decile and bottom decile, Decile 1-Decile 10.

All CTAs - Performance Persistence Tests - Ranking on OLS alpha, 1994-2010

	Alpha (%/ann.)	t-stat	p-value	Adj R^2	Mean (%/ann.)	IR	TE	SNP	SCMLC	BD10RT	BAATSY	PTFSB	PTFSF	PTFSC	PTFSR	PTFSS	GSCI
Decile 1	10.72	3.37	0.00	25.13	13.48	0.86	12.42	0.05	-0.05	0.31	-0.09	-0.01	0.06	0.08	-0.01	0.03	0.11
Decile 2	7.85	2.64	0.01	24.46	10.47	0.75	10.50	0.05	0.01	0.32	0.04	0.01	0.05	0.06	-0.01	0.02	0.07
Decile 3	7.38	2.73	0.01	26.86	9.70	0.76	9.69	-0.01	-0.01	0.33	0.03	0.01	0.05	0.06	-0.01	0.03	0.09
Decile 4	7.24	2.98	0.00	22.90	8.34	0.85	8.50	0.00	0.01	0.17	-0.01	0.02	0.04	0.03	-0.01	0.03	0.08
Decile 5	6.09	3.37	0.00	21.78	7.89	0.86	7.08	-0.02	0.02	0.15	0.08	0.02	0.03	0.02	0.00	0.03	0.07
Decile 6	7.13	3.99	0.00	33.99	7.72	1.08	6.61	0.00	0.01	0.15	0.05	0.04	0.04	0.01	0.00	0.04	0.08
Decile 7	6.76	4.13	0.00	34.74	7.15	1.10	6.14	0.01	0.01	0.16	0.06	0.03	0.03	0.03	-0.01	0.04	0.08
Decile 8	6.69	3.51	0.00	33.01	7.14	1.00	6.66	-0.01	0.03	0.16	0.05	0.05	0.03	0.02	-0.01	0.04	0.08
Decile 9	4.14	2.11	0.04	20.92	6.22	0.57	7.31	0.05	0.02	0.14	0.05	0.03	0.04	0.02	-0.01	0.02	0.05
Decile 10	9.40	2.32	0.02	28.27	6.96	0.82	11.53	-0.05	0.06	0.16	0.08	0.08	0.05	0.04	-0.03	0.06	0.05
Spread	**1.32**	**0.28**	**0.74**	**9.42**	**6.52**	**0.10**	**12.90**	**0.10**	**-0.10**	**0.15**	**-0.17**	**-0.08**	**0.01**	**0.04**	**0.01**	**-0.03**	**0.06**

All CTAs - Performance Persistence Tests - Ranking on t-statistics of alpha, 1994-2010

	Alpha (%/ann.)	t-stat	p-value	Adj R^2	Mean (%/ann.)	IR	TE	SNP	SCMLC	BD10RT	BAATSY	PTFSB	PTFSF	PTFSC	PTFSR	PTFSS	GSCI
Decile 1	7.79	3.61	0.00	23.56	10.66	0.90	8.62	0.00	0.00	0.26	0.05	-0.01	0.04	0.05	-0.01	0.03	0.07
Decile 2	6.65	3.28	0.00	26.90	8.59	0.88	7.59	0.04	-0.02	0.18	-0.04	0.02	0.04	0.04	-0.01	0.02	0.07
Decile 3	7.92	3.46	0.00	25.24	9.74	0.91	8.67	-0.04	0.01	0.17	-0.04	0.01	0.05	0.05	-0.01	0.02	0.06
Decile 4	6.81	2.09	0.04	24.70	9.31	0.67	10.15	0.04	-0.01	0.31	0.05	0.01	0.05	0.05	-0.02	0.02	0.10
Decile 5	8.47	3.48	0.00	25.43	9.81	0.82	10.29	0.03	0.02	0.30	0.00	0.03	0.06	0.04	-0.01	0.04	0.09
Decile 6	9.72	4.05	0.00	33.81	10.06	1.12	8.71	-0.04	0.02	0.23	0.09	0.04	0.06	0.03	-0.01	0.05	0.10
Decile 7	9.00	3.90	0.00	38.16	8.59	1.16	7.75	0.04	-0.02	0.19	0.04	0.06	0.04	0.03	-0.01	0.05	0.10
Decile 8	10.70	3.04	0.00	29.71	8.81	1.14	9.38	-0.03	0.01	0.19	0.09	0.07	0.02	0.05	-0.02	0.06	0.07
Decile 9	3.04	1.44	0.15	18.80	4.89	0.35	8.66	0.02	0.08	0.22	0.04	0.03	0.04	0.03	-0.01	0.02	0.05
Decile 10	2.53	1.46	0.15	22.65	4.49	0.42	5.97	0.03	0.00	0.04	0.07	0.01	0.04	0.02	-0.01	0.02	0.03
Spread	**5.26**	**2.26**	**0.04**	**5.10**	**6.17**	**0.61**	**8.56**	**-0.03**	**0.01**	**0.22**	**-0.02**	**-0.03**	**0.00**	**0.04**	**0.00**	**0.01**	**0.04**

Table 2.12: **Results of Performance Persistence by Strategy**

Table 2.12 reports the out-of-sample performance of sorting systematic and discretionary CTAs into quintile portfolios on the basis of two separate variables: on OLS alpha from the ten factor model used in this study and on the t-statistics of alpha. Portfolios are re-balanced annually. Reported results are for the sample period January 1994 to December 2010. Both alpha and t-statistics of alpha are measured using the most recent 24 months of data preceding the evaluation period. Portfolios are equally-weighted and weights are readjusted whenever a fund disappears from the sample. For each quintile, the table shows annualized alpha, t-statistics of alpha and respective p-value, the adjusted-R^2 from an OLS regression of portfolio return on the 10-factor model used in this study and annualized return in percentages. The table also shows the information ratio (IR), the tracking error, and the coefficients of the ten factors. Decile 1 comprises funds with the highest OLS alphas (t-statistics) and Decile 10 contains funds with the lowest alpha. The last row shows the spread calculated as the difference between the top decile and bottom decile, Decile 1-Decile 10.

SYSTEMATIC-Sorts on α																	
	Alpha (%/ann.)	**t-stat**	**p-value**	**Adj $\hat{R2}$**	**Mean (%/ann.)**	**IR**	**TE**	**SNP**	**SCMLC**	**BD10RT**	**BAATSY**	**PTFSB**	**PTFSF**	**PTFSC**	**PTFSR**	**PTFSS**	**GSCI**
Quintile 1	9.82	3.01	0.00	26.61	12.06	0.83	11.89	0.04	0.01	0.31	-0.08	0.02	0.07	0.07	-0.01	0.02	0.07
Quintile 2	8.60	3.10	0.00	30.86	9.23	0.85	10.08	-0.03	-0.03	0.30	0.02	0.03	0.06	0.06	-0.02	0.04	0.09
Quintile 3	8.61	3.90	0.00	30.51	9.06	1.00	8.65	-0.03	0.04	0.22	0.01	0.03	0.05	0.03	-0.01	0.04	0.09
Quintile 4	7.12	3.39	0.00	30.46	7.78	0.99	7.18	0.03	0.00	0.15	0.04	0.03	0.04	0.02	-0.01	0.04	0.08
Quintile 5	9.59	2.60	0.01	32.03	7.16	0.90	10.68	-0.01	0.04	0.18	0.05	0.08	0.05	0.04	-0.02	0.07	0.08
Spread	**0.23**	**0.06**	**0.94**	**7.85**	**4.91**	**0.02**	**10.26**	**0.05**	**-0.03**	**0.13**	**-0.13**	**-0.06**	**0.02**	**0.03**	**0.01**	**-0.04**	**-0.01**
SYSTEMATIC- t-statistics																	
	Alpha (%/ann.)	**t-stat**	**p-value**	**Adj $\hat{R2}$**	**Mean (%/ann.)**	**IR**	**TE**	**SNP**	**SCMLC**	**BD10RT**	**BAATSY**	**PTFSB**	**PTFSF**	**PTFSC**	**PTFSR**	**PTFSS**	**GSCI**
Quintile 1	7.44	3.27	0.00	27.59	10.07	0.85	8.72	0.03	0.00	0.24	-0.02	0.01	0.06	0.05	-0.01	0.02	0.05
Quintile 2	9.52	2.83	0.01	28.94	9.84	0.90	10.54	-0.03	0.02	0.28	-0.01	0.03	0.06	0.06	-0.02	0.04	0.09
Quintile 3	10.20	3.89	0.00	33.19	9.84	0.97	10.54	-0.04	0.02	0.31	0.04	0.04	0.06	0.04	-0.01	0.05	0.11
Quintile 4	11.52	4.12	0.00	36.94	9.82	1.24	9.29	0.02	-0.01	0.16	-0.01	0.06	0.05	0.05	-0.02	0.06	0.09
Quintile 5	5.06	2.36	0.02	24.90	5.83	0.59	8.52	0.02	0.04	0.19	0.04	0.03	0.04	0.03	-0.01	0.04	0.07
Spread	**2.38**	**1.18**	**0.30**	**0.73**	**4.23**	**0.31**	**7.67**	**0.00**	**-0.04**	**0.05**	**-0.06**	**-0.02**	**0.01**	**0.02**	**0.00**	**-0.02**	**-0.01**
DISCRETIONARY-Sorts on α																	
	Alpha (%/ann.)	**t-stat**	**p-value**	**Adj $\hat{R2}$**	**Mean (%/ann.)**	**IR**	**TE**	**SNP**	**SCMLC**	**BD10RT**	**BAATSY**	**PTFSB**	**PTFSF**	**PTFSC**	**PTFSR**	**PTFSS**	**GSCI**
Quintile 1	12.48	4.68	0.00	18.40	14.36	1.20	10.42	0.01	-0.03	0.16	0.10	-0.02	0.02	0.05	-0.01	0.04	0.17
Quintile 2	1.72	1.02	0.31	9.67	6.28	0.34	5.09	0.06	0.07	0.04	0.06	-0.01	0.01	0.00	0.01	0.00	0.04
Quintile 3	1.01	0.61	0.54	7.70	4.85	0.19	5.20	0.06	-0.05	0.05	0.01	0.01	0.01	0.02	0.00	-0.01	0.01
Quintile 4	1.10	1.14	0.26	12.19	3.84	0.28	3.90	0.00	0.00	0.08	0.10	0.02	0.01	0.01	0.00	0.01	0.02
Quintile 5	3.97	1.27	0.20	-0.63	6.63	0.38	10.36	0.02	0.04	0.15	-0.01	0.01	0.02	0.01	-0.01	0.01	-0.02
Spread	**8.51**	**2.34**	**0.03**	**10.43**	**7.73**	**0.68**	**12.56**	**-0.02**	**-0.06**	**0.01**	**0.11**	**-0.03**	**-0.01**	**0.05**	**0.00**	**0.04**	**0.19**
DISCRETIONARY- t-statistics																	
	Alpha (%/ann.)	**t-stat**	**p-value**	**Adj $\hat{R2}$**	**Mean (%/ann.)**	**IR**	**TE**	**SNP**	**SCMLC**	**BD10RT**	**BAATSY**	**PTFSB**	**PTFSF**	**PTFSC**	**PTFSR**	**PTFSS**	**GSCI**
Quintile 1	7.00	3.21	0.00	14.34	9.69	0.80	8.75	-0.03	0.02	0.16	0.04	-0.02	0.02	0.03	-0.01	0.03	0.13
Quintile 2	5.35	1.99	0.05	8.66	8.79	0.67	7.94	0.06	-0.02	0.17	0.20	-0.01	0.01	0.02	0.00	0.03	0.07
Quintile 3	1.72	0.58	0.56	6.70	5.85	0.25	6.89	0.04	-0.01	0.11	0.07	-0.01	0.02	0.03	0.00	0.00	0.02
Quintile 4	5.81	2.56	0.01	1.47	8.14	0.74	7.84	0.05	0.02	0.12	0.03	0.03	0.00	0.02	0.00	0.01	0.01
Quintile 5	-1.11	-0.62	0.53	5.12	2.17	-0.19	5.85	0.02	-0.02	0.03	-0.03	0.01	0.03	0.00	-0.01	0.00	0.00
Spread	**8.12**	**2.91**	**0.01**	**7.36**	**7.51**	**0.84**	**9.69**	**-0.05**	**0.04**	**0.13**	**0.07**	**-0.03**	**0.00**	**0.02**	**0.00**	**0.03**	**0.12**

Table 2.13: **Results of Performance Persistence by Strategy: Equally and Value-Weighted Portfolios**

Table 2.13 reports the results by strategy of sorting funds into portfolios on the basis of past t-statistics of OLS alpha with quarterly, semiannually and annual rebalancing. The t-statistics of alpha are measured using the most recent 24 months of data preceding the evaluation period. Portfolios are calculated for equally-weighted and value-weighted portfolios so the weights are readjusted whenever a fund disappears from the sample. For each portfolio the table reports annualized alphas and t-statistics of alpha below (in italics) for the top, bottom and spread portfolios for each strategy. Reported results are for the sample period January 1994 to December 2010.

BOTTOM QUINTILE	Equally Weighted			Value Weighted			TOP QUINTILE Equally Weighted			Value Weighted		
Strategy	3-month	6-month	12-month	3-month	6-month	12-month	3-month	6-month	12-month	3-month	6-month	12-month
All funds	6.59	4.37	2.53	10.08	3.90	0.98	5.69	6.80	7.79	10.18	9.14	9.87
	1.67	*2.12*	*1.46*	*3.22*	*1.29*	*0.38*	*1.77*	*3.18*	*3.61*	*3.70*	*3.70*	*4.05*
Systematic	8.98	6.95	5.06	7.14	4.28	1.48	7.22	7.60	7.44	10.75	10.14	12.00
	3.69	*2.79*	*2.36*	*2.04*	*1.37*	*0.53*	*3.40*	*3.45*	*3.27*	*3.85*	*3.87*	*4.63*
Systematic Trend	8.90	7.19	5.04	6.76	3.60	0.52	7.20	7.97	8.98	11.49	10.87	12.06
	3.31	*2.56*	*2.16*	*1.98*	*1.17*	*0.19*	*3.26*	*3.53*	*4.18*	*4.25*	*4.29*	*4.60*
Systematic S-T	2.51	2.04	-0.37	2.86	1.82	0.73	10.05	11.96	9.43	12.57	14.04	13.46
	1.98	*1.55*	*-0.38*	*1.61*	*1.21*	*0.41*	*4.02*	*4.70*	*3.59*	*5.39*	*6.40*	*4.54*
Systematic M-T	9.23	9.03	6.02	13.02	10.54	4.14	7.84	6.99	7.42	11.85	12.32	13.73
	3.27	*3.21*	*2.26*	*3.70*	*3.60*	*1.67*	*2.98*	*2.54*	*2.84*	*3.75*	*3.70*	*4.39*
Systematic L-T	11.84	11.52	7.27	14.03	5.18	5.12	9.17	8.89	9.18	12.51	12.72	9.04
	2.49	*2.27*	*1.77*	*2.43*	*1.04*	*1.11*	*1.79*	*1.87*	*2.32*	*3.04*	*3.06*	*1.98*
Systematic Spread	8.28	6.87	3.11	4.55	5.9	5.87	2.54	3.74	7.02	2.17	1.45	4.39
	2.34	*1.92*	*0.66*	*1.47*	*1.93*	*1.92*	*0.64*	*1.15*	*2.81*	*0.85*	*0.57*	*1.55*
Systematic Pattern	11.22	11.72	16.08	11.13	14.23	13.88	16.5	15.69	10.42	2.13	19.14	8.79
	2.09	*1.81*	*2.38*	*2.91*	*-0.06*	*3.07*	*1.73*	*1.54*	*0.92*	*0.48*	*0.02*	*2.1*
Discretionary	-1.79	-1.94	3.97	1.55	1.7	0.47	7.95	6.97	12.48	7.83	8.52	5.54
	-1.29	*-1.23*	*2.34*	*1.06*	*0.87*	*0.24*	*3.75*	*3*	*4.68*	*3.22*	*3.98*	*2.74*
Discretionary Fund	0.67	2.84	0.85	-0.25	2.47	2.11	4.45	5.26	-4.39	6.34	5.86	0.12
	0.19	*0.96*	*0.34*	*-0.09*	*0.79*	*0.73*	*0.86*	*0.98*	*-0.8*	*2.33*	*2.12*	*0.03*
Discretionary Fund & T	0.65	0.45	5.33	4.26	5.73	2.71	10.43	12.16	11.38	10.52	7.91	5.33
	0.25	*0.13*	*0.80*	*1.47*	*1.81*	*0.80*	*2.97*	*2.70*	*2.30*	*4.08*	*2.74*	*1.44*
Discretionary Tech	1.55	0.00	1.87	9.61	2.34	5.08	11.37	11.82	11.16	2.37	8.93	5.88
	0.59	*0.00*	*0.75*	*3.10*	*1.50*	*2.40*	*1.99*	*2.37*	*3.28*	*1.44*	*3.01*	*1.68*
Discretionary Spread	-3.27	-3.83	-2.88	-2.63	-0.61	1.26	8.33	4.32	-1.62	4.21	3.17	2.07
	-0.97	*-1.10*	*-0.85*	*-1.36*	*-0.25*	*0.62*	*2.65*	*1.07*	*-0.38*	*2.25*	*1.50*	*0.93*
Options	4.29	2.60	8.45	9.10	7.53	3.93	-2.67	-5.99	-18.00	-2.28	-0.27	-2.04
	1.22	*0.76*	*2.21*	*1.64*	*1.37*	*0.68*	*-0.40*	*-0.81*	*-2.31*	*-0.52*	*-0.06*	*-0.55*

	Equally Weighted			Value Weighted		
SPREAD	3-month	6-month	12-month	3-month	6-month	12-month
All funds	-0.86	2.43	5.26	0.10	5.24	8.88
	-0.20	*0.96*	*2.26*	*0.03*	*1.36*	*2.40*
Systematic	-1.76	0.66	2.38	3.61	5.86	10.52
	-0.97	*0.34*	*1.18*	*0.84*	*1.49*	*2.87*
Systematic Trend	-1.70	0.78	3.93	4.73	7.27	11.54
	-0.78	*0.35*	*2.05*	*1.18*	*2.05*	*3.28*
Systematic S-T	7.54	10.02	9.80	9.72	12.22	12.74
	2.85	*3.74*	*2.23*	*3.69*	*4.79*	*4.86*
Systematic M-T	-1.38	-2.04	1.40	-1.18	1.78	9.58
	-0.58	*-0.82*	*0.61*	*-0.45*	*0.85*	*3.47*
Systematic L-T	-2.67	-2.63	1.91	-1.52	7.54	3.92
	-0.50	*-0.55*	*0.50*	*-0.26*	*1.46*	*0.69*
Systematic Spread	-6.36	-3.97	1.7	-2.38	-4.45	-1.48
	-1.43	*-0.94*	*0.31*	*-0.56*	*-1.06*	*-0.3*
Systematic Pattern	6.22	5.26	-3.92	-9.01	-6	-5.09
	0.57	*0.4*	*-0.37*	*-1.41*	*-0.86*	*-0.81*
Discretionary	9.74	8.91	8.51	6.28	6.83	5.07
	4.12	*3.4*	*2.34*	*2.16*	*2.22*	*1.62*
Discretionary Fundamental	3.78	2.42	-5.24	6.58	3.39	-2
	0.61	*0.44*	*-0.89*	*1.69*	*0.81*	*-0.4*
Discretionary Fund & Tech	9.67	12.02	6.41	6.26	2.18	2.62
	2.16	*2.01*	*0.75*	*1.42*	*0.45*	*0.50*
Discretionary Tech	8.94	10.86	8.72	7.24	6.59	0.80
	1.48	*2.07*	*2.08*	*2.23*	*1.95*	*0.20*
Discretionary Spread	11.88	8.59	0.57	6.84	3.78	0.82
	3.10	*1.71*	*0.10*	*2.43*	*1.06*	*0.27*
Options	-7.11	-8.44	-26.91	-11.38	-7.8	-5.97
	-0.86	*-0.97*	*-2.76*	*-1.8*	*-1.14*	*-0.89*

Table 2.14: **Performance of Portfolios of CTAs Formed on Size**

Table 2.14 reports the results of equally-weighted portfolios of CTAs formed on fund size for the period January 1994 to December 2010. Funds are sorted each year in terciles based on their mean assets under management in the previous 24 month period. The ten factor model was used to assess the out-of-sample performance of CTAs. t-statistics for the significance of alpha are reported in parentheses.

One Year Evaluation Period				
Systematic				
	Tercile 1	**Tercile 2**	**Tercile 3**	**Tercile 3 - Tercile 1**
	5.58	8.02	9.03	3.46
	(2.74)	(3.73)	(3.89)	(2.95)
Adj R^2	37.33	43.14	33.37	
Discretionary	**Tercile 1**	**Tercile 2**	**Tercile 3**	**Tercile 3 - Tercile 1**
	7.62	3.12	4.7	-2.91
	(2.71)	(2.17)	(4.23)	(-1.02)
Adj R^2	15.21	11.62	22.03	

Six Months Evaluation Period				
Systematic				
	Tercile 1	**Tercile 2**	**Tercile 3**	**Tercile 3 - Tercile 1**
	6.05	7.86	8.8	2.75
	(3.12)	(3.64)	(3.96)	(2.59)
Adj R^2	39.06	42.43	33.03	
Discretionary				
	Tercile 1	**Tercile 2**	**Tercile 3**	**Tercile 3 - Tercile 1**
	8.41	3.62	4.97	-3.45
	(2.95)	(2.46)	(4.48)	(-1.19)
Adj R^2	14.32	0.02	23.58	

Figure 2.1: **Scaled Recursive Residuals for the CTAs**

Figure 2.1A. shows a plot scaled recursive residuals for the equally-weighted index of CTA returns. Figure 2.1B. shows a plot of scaled recursive residuals for the value-weighted index of CTA returns. Figure 2.1C. shows a plot of scaled recursive residuals for the value-weighted index of discretionary CTA returns.

Figure 2.1A

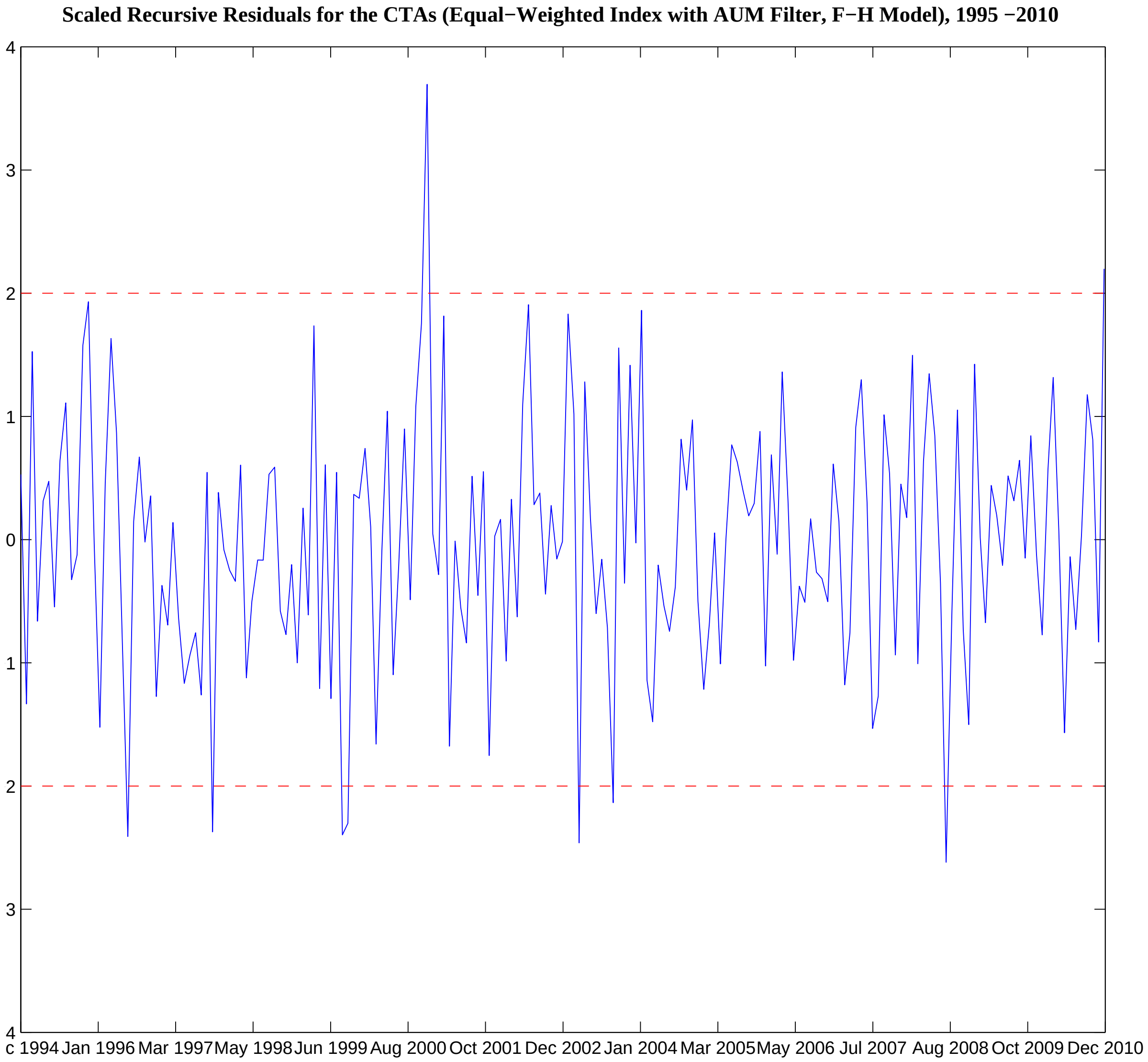


Figure 2.1B

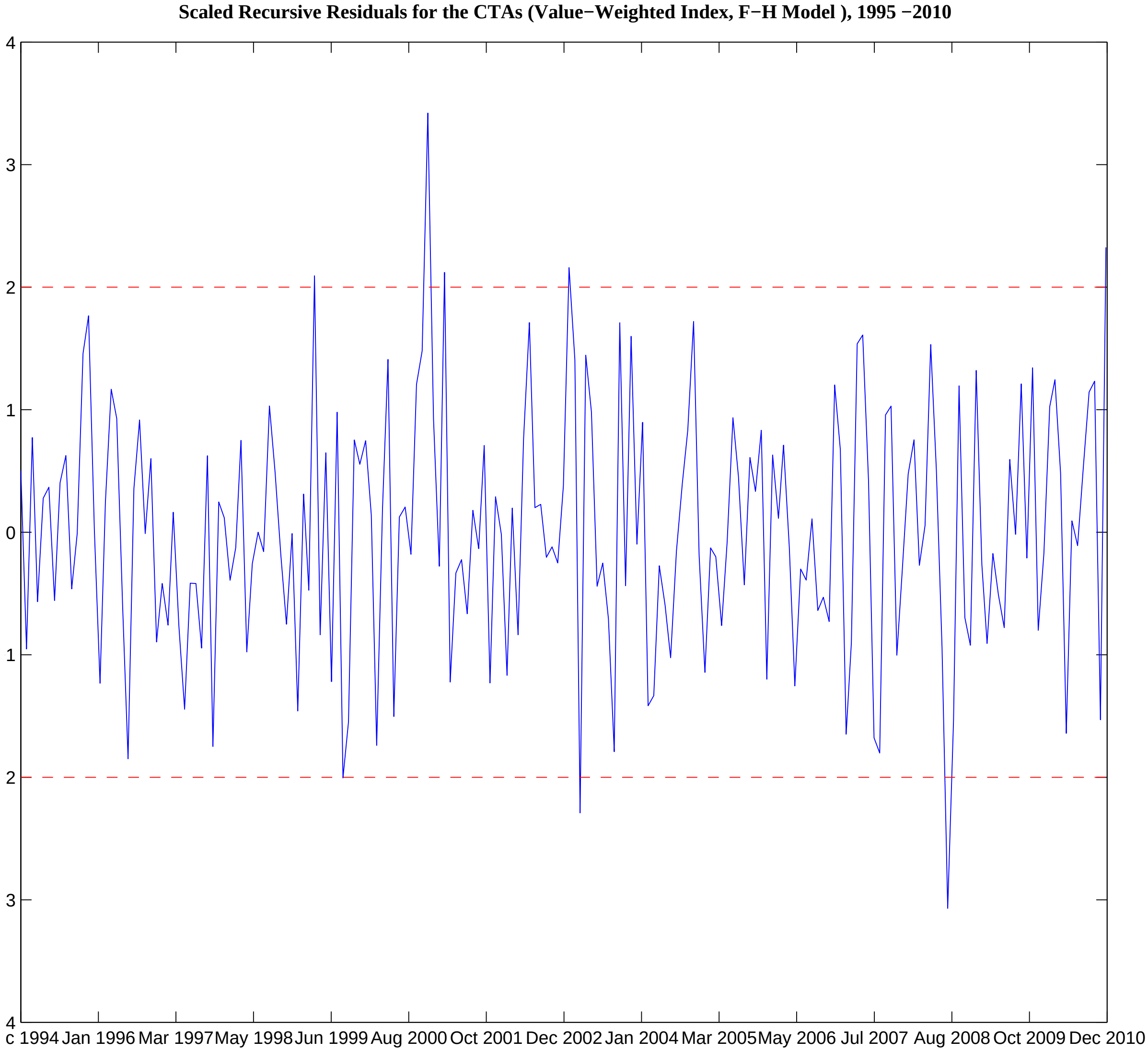

Scaled Recursive Residuals for the CTAs (Value−Weighted Index, F−H Model), 1995 −2010
4
3
2
1
0
1
2
3
4
c 1994
Jan 1996
Mar 1997
May 1998
Jun 1999
Aug 2000
Oct 2001
Dec 2002
Jan 2004
Mar 2005
May 2006
Jul 2007
Aug 2008
Oct 2009
Dec 2010

Figure 2.1C

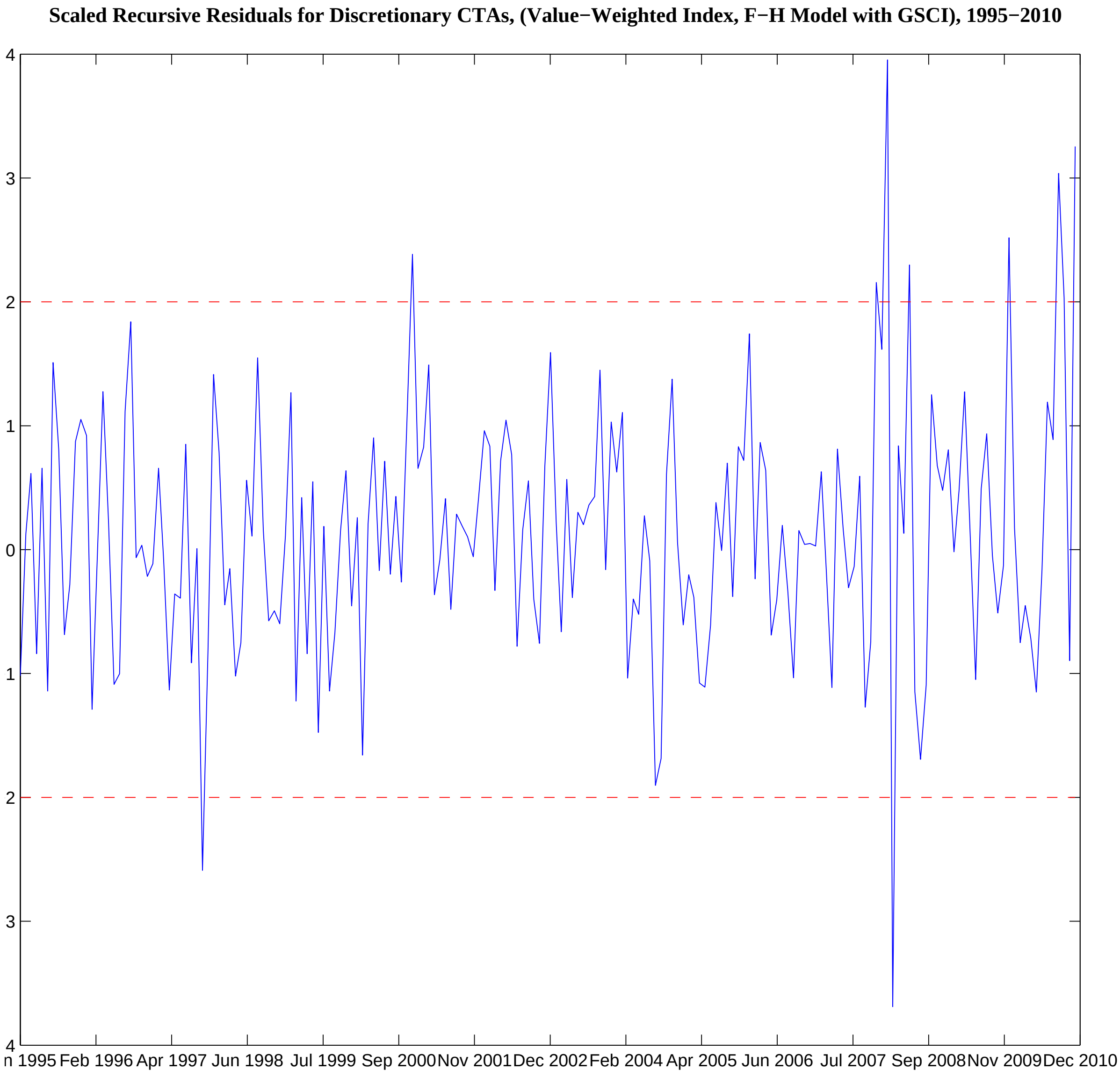

Scaled Recursive Residuals for Discretionary CTAs, (Value−Weighted Index, F−H Model with GSCI), 1995−2010
4
3
2
1
0
1
2
3
4
n 1995
Feb 1996
Apr 1997
Jun 1998
Jul 1999
Sep 2000
Nov 2001
Dec 2002
Feb 2004
Apr 2005
Jun 2006
Jul 2007
Sep 2008
Nov 2009
Dec 2010

Figure 2.2: **Total AUM for the CTA Industry**

Figure 2.2 shows a plot of total assets under management and growth in the number of funds for the managed futures industry, 1993-2010. Data from the BarclayHedge database.

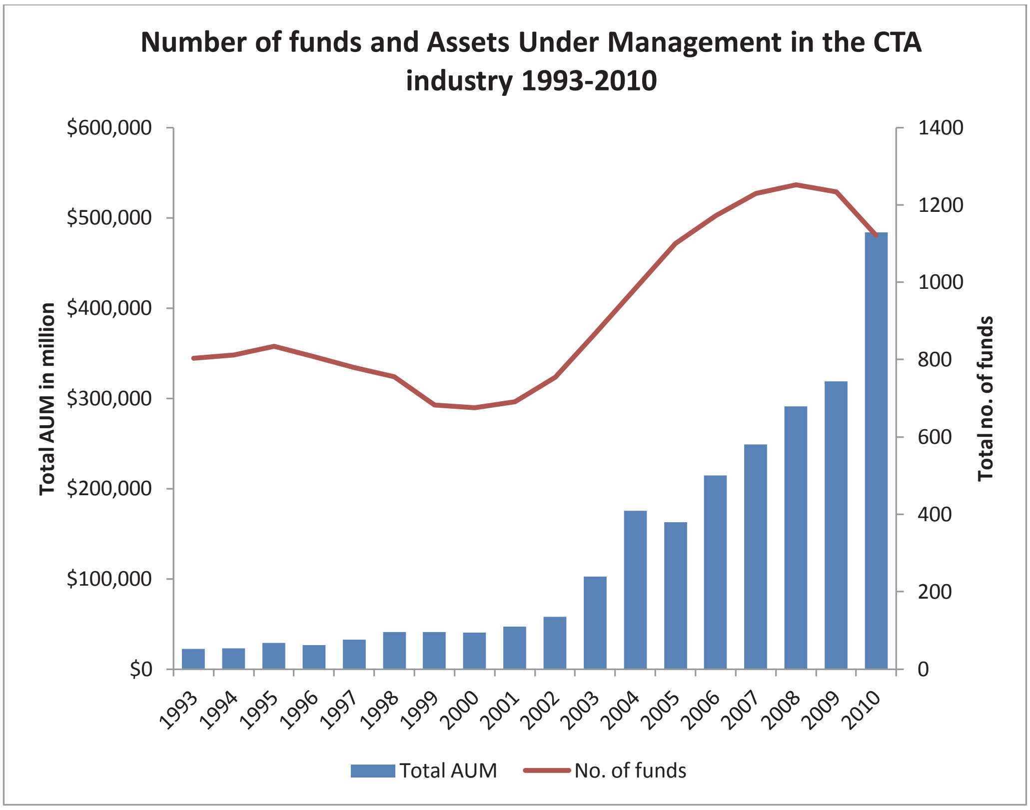


Figure 2.3: **CTA Mean Assets Under Management**

Figure 2.3 shows a plot of mean assets under management for the managed futures industry, 1993-2010. Data from the BarclayHedge database.

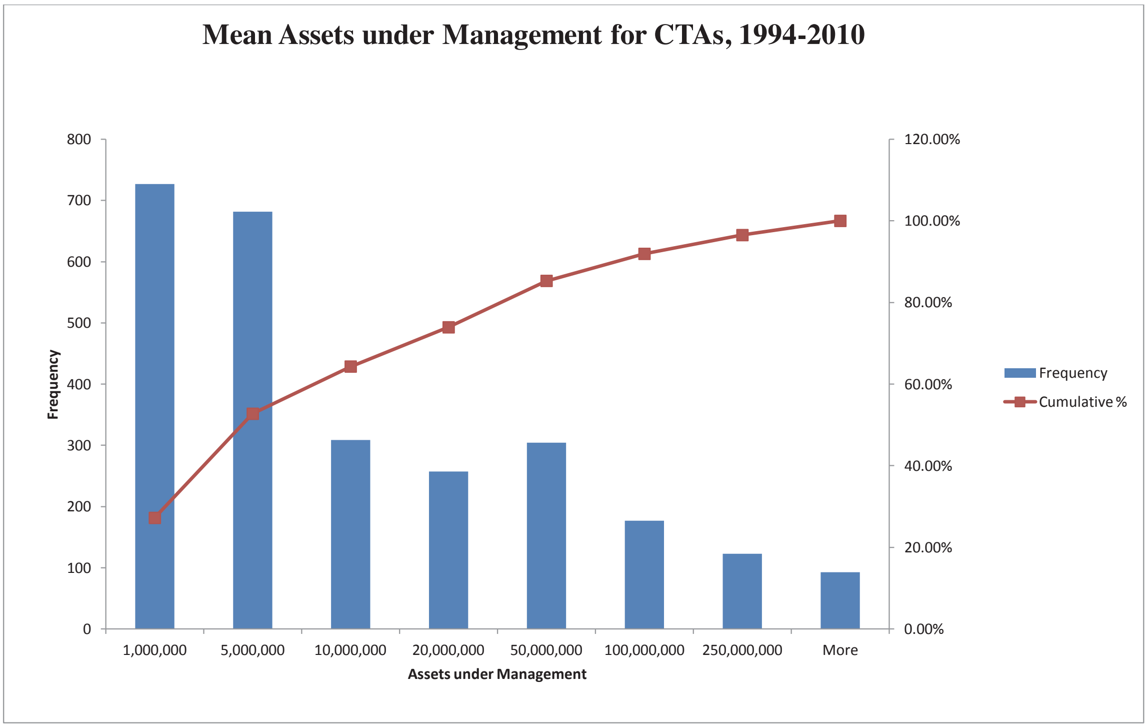


Figure 2.4: **Cumulative Excess Returns: Equally-Weighted and Value-Weighted Portfolios**

Figure 2.4 shows a plot of Equally-Weighted and Value-Weighted Portfolios of Excess Returns of CTAs. Data from the BarclayHedge database for the January 1994 to December 2010 period.

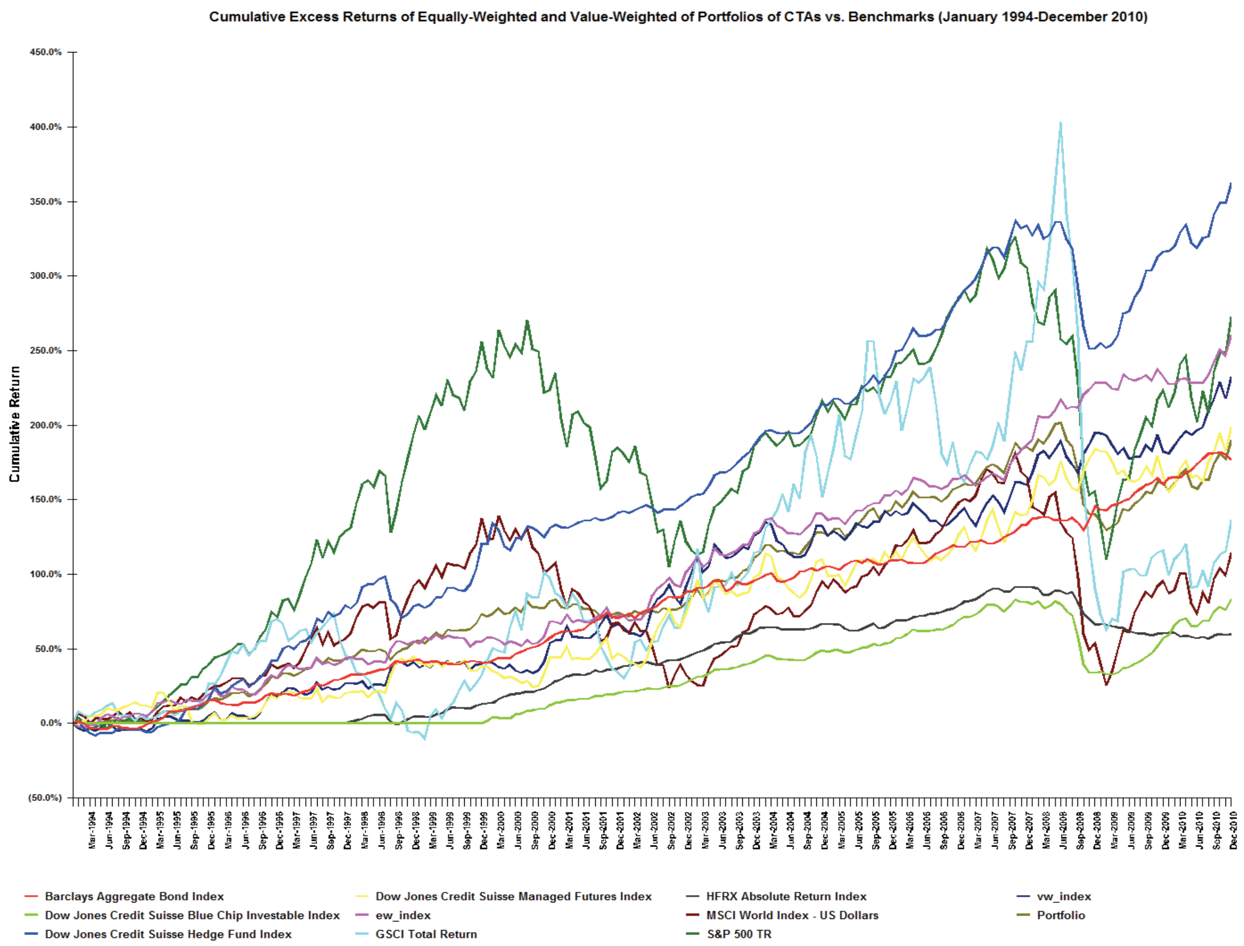


Figure 2.5: **Cumulative Excess Returns: Equally-Weighted and Value-Weighted Portfolios for Systematic and Discretionary Funds**

Figure 2.5 shows a plot of Equally-Weighted and Value-Weighted Portfolios of Excess Returns of CTAs. Data from the BarclayHedge database for the January 1994 to December 2010 period.

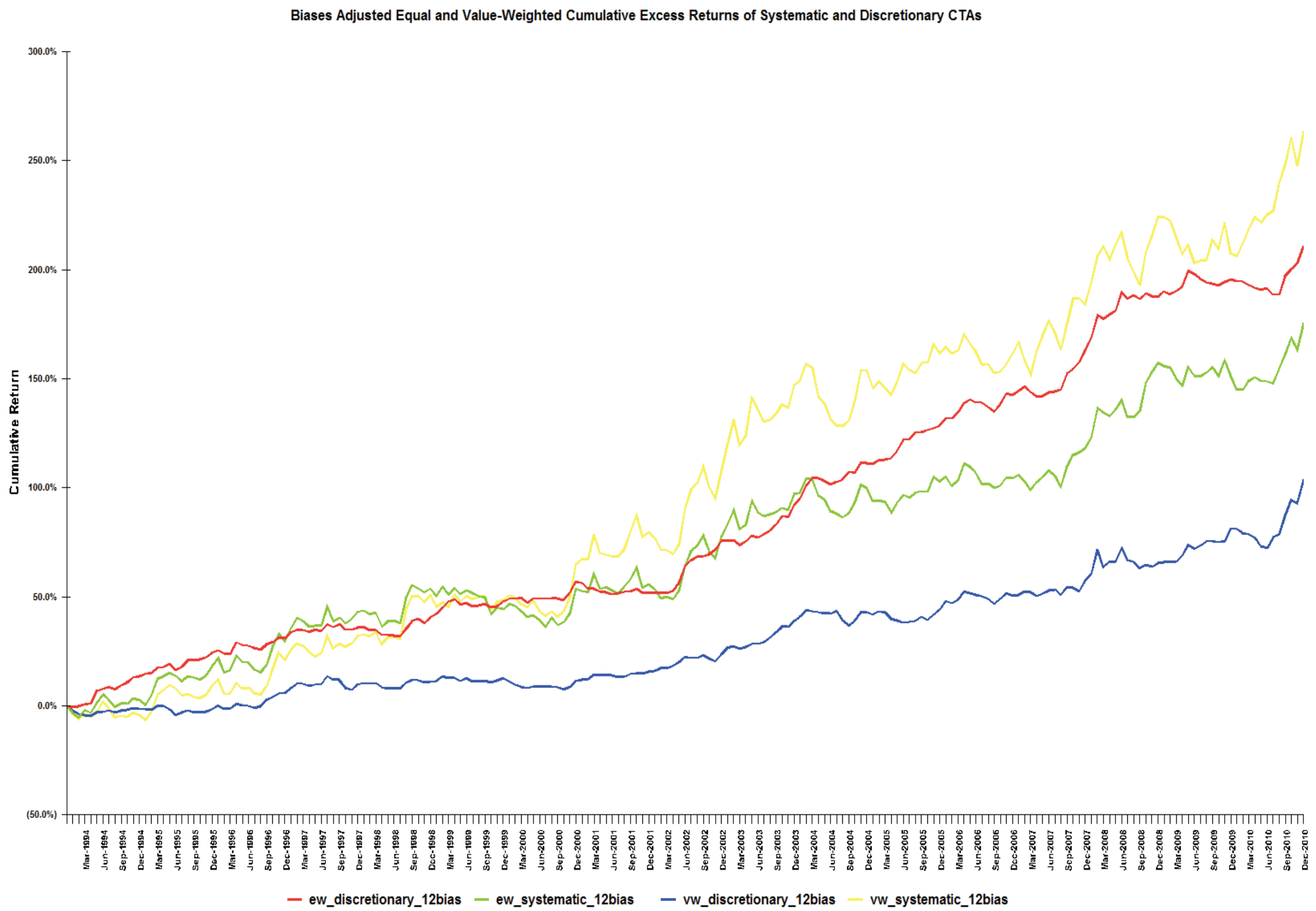
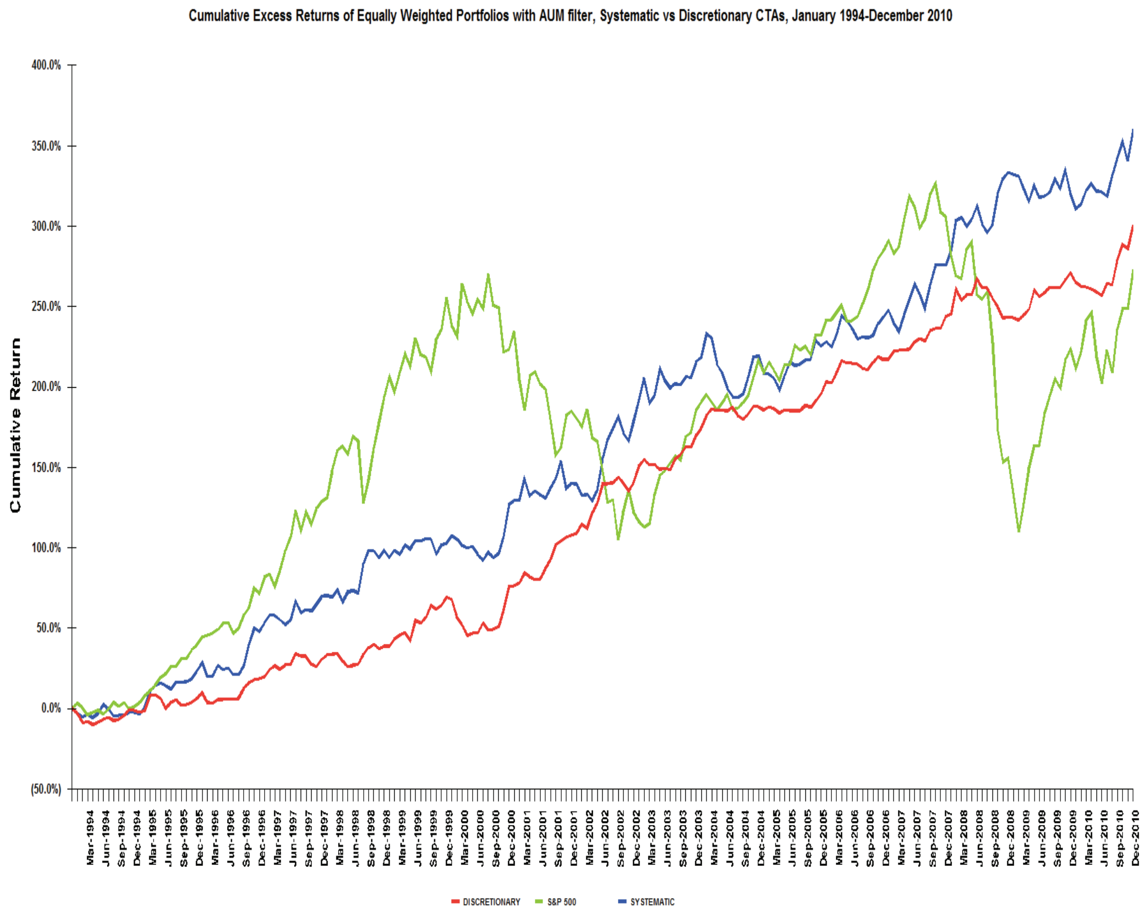


Figure 2.6: **Cumulative Excess Returns: Equally-Weighted Portfolios adjusted for biases and with AUM filter for Systematic and Discretionary Funds**

Figure 2.6 shows a plot of Equally-Weighted Portfolios of Excess Returns of Systematic and Discretionary CTAs adjusted for instant history and survivorship biases and with AUM filter. Data from the BarclayHedge database for the January 1994 to December 2010 period.



Chapter 3

Flow-Performance Relationship of Commodity Trading Advisors

3.1 Introduction

Much of the literature on Commodity Trading Advisors has focused on performance attribution and its persistence (see Irwin and Brorsen (1998), Brown et al. (2001) and Gregoriou et al. (2010)). According to recent media reports, however, CTAs were one of the few profitable trading strategies during the financial crisis of 2008.[1] Figure 3.1 shows that as a result of this good performance, CTAs received a large inflow of assets thereafter despite a simultaneous decrease in the number of funds. Little attention has been paid to CTA fund flows and the factors relating to them in the academic literature. Brown et al. (2001) and Do et al. (2011) are the only studies that have considered the fund flow-performance relationship. CTAs appear to have regained investors' interest in the last few years. It is, therefore, of interest to study the behaviour of investor flows to individual CTAs and the factors that investors consider before placing their money into these funds.

In the mutual fund literature the fund flow-performance relationship has been extensively analyzed. For example, Ippolito (1992), Chevalier and Ellison (1997) and Sirri and Tufano (1998) have analyzed the driving factors of flows into the mutual fund industry and found that these are positively related to past relative performance. However, this relationship is found to be nonlinear and different across different performance regions. For example the authors find that for the top performers - funds in the top performance quintile - performance is associated with economically and statistically significant inflows i.e. a positive and statistically significant coefficient. That is top performing funds that experience good performance will further increase in size. In the lowest quintile however, the association is weak and insignificant. This is seen graphically in Figure 3.12[2]. The relationship between flows and performance is only significant for funds in the top performance region and insignificant in the low performance region (note absence of slope in the leftmost portion of flow/performance graph) producing a con-

[1]The Financial Times, March 2011. "CTAs: "True diversifiers" with returns to boot".

[2]Reproduced from Sirri and Tufano (1998).

vex flow-performance relationship. The authors attribute this to investors chasing past performance by disproportionately selecting high performing funds while failing to flee from lesser performing funds at the same rate (i.e. absence of significant slope). Other significant factors are the volatility of returns and fees which negatively impact flows. In the hedge fund literature the flow-performance relationship has also been extensively analysed albeit with mixed results. For example using annual hedge fund data Agarwal, Daniel and Naik (2003) also found a positive and convex flow performance relationship for hedge funds: well performing funds in the top quintile attract significantly greater inflows than their poorly performing counterparts. On the other hand, using a single linear response equation, Goetzmann, Ingersoll and Ross (2003) found the relationship between flows and past performance to be negative: managers refuse new money after a good year and seek additional funding after a bad year. The authors propose that in a stylized framework in a which hedge fund manager exploits limited arbitrage opportunities, capital can be put to a profitable use only up to the point after which any additional capital inflows will lead to an increase in systematic risk. Therefore the authors argue that since hedge fund technology is non-linear, managers may refuse new money when they do well. However, when the authors examine the differential response of new money to past performance by allowing coefficients to differ for different performance quintiles of lagged returns as in the mutual fund framework, they find that the coefficient is negative only in the high performance region and positive in the low performance region. That is, new money flows out of the good performers producing a concave flow-performance relationship. This, the authors argue, provides support for the hypothesis that good performers may not readily accept new money due to limited arbitrage opportunities. This highlights the need to account for the nonlinearity of the relationship between flows and past performance. Getmansky (2005) also finds a concave fund flow-performance relationship for hedge funds, although the response of flows to the top performers is insignificant rather than negative as in Goetzmann et al. (2003): top performing funds do not grow proportionately as much as the average fund in the market. On the other hand, Baquero and Verbeek (2009) find that the response of flows to past performance is invariant to the performance region to which a fund belongs to, that is they find a strictly linear response. Finally, Ding, Getmansky, Liang and Wermers (2009) attempt to reconcile these differences in results in the response of flows to past hedge fund performance. The authors argue that differences in the liquidity restrictions of hedge funds, such as fund lockups, affect the shape of the flow-performance relationship: funds with tighter share restrictions have a concave flow-performance relationship and funds without any restrictions have a convex flow-performance relationship.

Studies of CTA fund flows are rather limited as most of the literature has focused on performance attribution. Lajbcygier (2008) and Do et al. (2011) are the only studies that have looked at the factors determining CTA flows and have found a positive relationship between fund flows and past performance. However, the authors have not examined if this response is differential across different performance regions as was found in the mutual fund, hedge fund and private equity (See Kaplan and Schoar (2003)) industries. CTAs however are different to both hedge funds and mutual funds. From a regulatory point of view, CTAs are less transparent and less regulated than mutual funds. That said, momentum, the main trading style of many CTAs has been well analyzed by researchers, yet their trading activities are still somewhat of a black box for many unsophisticated investors and are far less transparent than those of the mutual funds. The convex flow-performance relationship found in the mutual fund industry has been attributed to the transparency of the trading styles and the liquidity of the industry. On the other hand, the concave flow-performance relationship found by academic research for hedge funds has been attributed to extensive investor search costs, limits to the investment strategies and tighter share restrictions. Commodity Trading Advisors, however, trade in the most liquid instruments, futures and forwards, the markets for which are very deep and liquid. As a result, the subscription and redemption notices tend to be much shorter for many CTAs than for hedge funds. Academic studies have also found managed futures to have less illiquidity than hedge funds, Getmansky, Lo and Makarov (2004) and Bollen and Whaley (2009). From a structural and functional point of view this places CTAs somewhere between hedge funds and mutual funds. These differences may have implications for how investors will allocate their portfolios across different funds. Hence this leads to a question: What are the determinants of money-flows in CTAs and in particular how are they related to fund's past performance?

In this chapter I analyze the response of quarterly and yearly money flows to the past relative performance of CTAs. In particular, following earlier literature on hedge funds and mutual funds, I look at whether this relationship is differential in different performance regions. Whilst Ding, Getmansky, Liang and Wermers (2009) focus on annual data for hedge funds, I use both quarterly and yearly data to study the flow-performance relationship of CTAs. Baquero and Verbeek (2009) also use quarterly and annual data for hedge funds and show that the shape of the flow-performance relationship differs depending on the time horizon employed in the study. Accordingly, I use piecewise linear regression to model the non-linearity of the flow-performance relationship and apply it to quarterly as well as yearly data. I also look at the possible effect of the share restrictions in the CTA industry on the flow-performance relationship. As argued by Ding et al. (2009), in the presence of share restrictions, the flow-performance relationship of hedge funds becomes concave, whilst in the absence of share restrictions it remains convex, as previously documented in the literature. Since the BarclayHedge database has incomplete information on CTA share restrictions, I model the restrictions using Getmansky et al.'s (2004) asset illiquidity parameter, θ_0 and show that there are a few CTA strategies, such as systematic spread/relative value and discretionary spread/relative value strategies, that do indeed have tighter share restrictions than the other CTA strategies. These share restrictions, however, have a limited effect on the shape of the flow-performance relationship in the CTA industry. Instead I argue that, in the CTA industry, the strategy of the CTA and the size of the fund have a more significant impact on the shape of the flow-performance relationship. For the quarterly data, I find that the relationship is concave and largely driven by large CTAs. However, these fund flows are influenced by the strategy that the CTAs belong to. By extending the analysis of fund flow-performance relationship to individual CTA strategies, I find that systematic CTAs have a linear quarterly flow-performance relationship whilst discretionary CTAs have a concave quarterly relationship and that this is mainly driven by small discretionary CTAs.

In the last section I also address the effect of flows on performance persistence and, to this end, I look at the smart money effect in the CTA industry. Smart money is defined as the ability of investors to infer the skill of the fund managers and therefore to allocate assets more smartly between those fund managers, thereby receiving a greater return in the next period than other "naive" investors. The smart money effect has been extensively documented in the mutual fund and hedge fund industry. Gruber (1996) and Zheng (1999) studied the smart money effect on the mutual fund industry and found that flows predicted future returns. Sapp and Tiwari (2004), however, attribute this effect to the momentum of the strategies of mutual funds, whilst Frazzini and Lamont (2008), who have more recently looked at the long-term performance of smart money, find that it quickly reverses. In the hedge fund industry, the findings have been rather mixed. Baquero and Verbeek (2009) find no smart money effect in the TASS hedge fund database, whilst Ding et al. (2009) find some smart money effect but only in the absence of share restrictions. Ozik and Sadka (2010) find a smart money effect for hedge funds in the TASS database for the period 1999-2008 but show that the smart money strategy predominantly stems from funds that have a higher flow-impact coefficient. Moreover, the effect is more apparent for outflows than inflows. Ahoniemi and Jylha (2011) also find evidence of smart money in the TASS hedge fund data, although their focus is on the contemporaneous direction of causality and thus no smart money effect is found past the months of the flows. In the CTA literature only one study has thus far addressed the effect of smart money. Do, Faff, Lajbcygier and Veeraraghavan (2010) analysed the CTA flow data in the BarclayHedge database for the period 1975 to April 2006, finding no evidence of smart money.

Turning to the issue of the effect of hedge fund flows on performance persistence, according to Berk and Green's (2004) model for mutual funds, persistence in the mutual fund industry is rather indicative of the lack of competition in the supply of capital. Thus, Baquero and Verbeek (2009) find that, at the quarterly horizon, where response of money flows to hedge funds is weaker, there is evidence of performance persistence for better performing funds but this persistence disappears at the annual horizon as investor flows catch up. Fung, Hsieh, Naik and Ramadorai (2008) also find that the alpha of fund of hedge funds tends to zero with an increase in the supply of capital. In the second part of this thesis, I found that there is performance persistence for CTAs at the annual horizon and that performance persistence is driven by large systematic funds, whereas for discretionary funds it is driven by small funds. In this chapter I analyze the effect of flows on the performance persistence of large funds at quarterly and annual horizons and find opposite results to those of Baquero and Verbeek (2009). Systematic CTAs with large inflows show no performance persistence at a quarterly horizon but evidence of performance persistence at an annual horizon. For discretionary CTAs the pattern is somewhat similar to hedge funds. I find no evidence, however, of any smart money effect in the CTA industry, despite using two different methodologies and applying them to various CTA strategies. My results indicate that investors do not always appear to be able fully to exploit the liquidity that CTAs provide.

Although fund flow-performance relationship and the smart money effect have been well addressed in the hedge fund industry, to the best of my knowledge the effect of flows on performance and persistence has not been rigorously examined in the CTA literature. So far, Do, Faff, Lajbcygier and Veeraraghavan (2010) is the only study that exclusively addresses this issue. In this study, I therefore provide several contributions to the CTA literature. Whilst Do et al. (2010) also use the BarclayHedge database strategy classifications to study CTAs, as I have shown previously in this thesis, most of the funds in the BarclayHedge database require manual reclassification. To that end I hand-collected a substantial amount of missing information by direct contact with the industry professionals to ascertain the exact strategy classification of each fund. This thesis, therefore, uses the most thoroughly constructed CTA strategy classifications that allows a more robust study of the differences between two important strategies among CTAs: systematic and discretionary. Furthermore, unlike previous studies in the CTA literature I apply the flow-performance relationship using quarterly as well as annual data and find that the relationship at the quarterly horizon is different for some strategies than for others. To the best of my knowledge, I am also the first to test for the effect of flows on performance persistence in the CTA industry. My results show that CTAs have long term performance persistence rather than short-term performance persistence with large inflows of capital and that this is mainly driven by large systematic CTAs.

Finally, this chapter is related to the literature on capacity constraints. To the best of my knowledge this is the first paper to look at capacity constraints within various CTA strategies. In the hedge fund literature, capacity constraints have been studied by Fung, Naik and Ramadorai (2008) who find evidence of diminishing alpha with an increase in asset flows for fund of hedge funds. Naik, Ramadorai and Stromquist (2007) further examine capacity constraint at the level of hedge fund strategies and find four hedge fund strategies that are capacity constrained: Relative Value, Directional Traders, Emerging Markets and Fixed Income. Managed futures, they document, do not appear to suffer from capacity constraints. This chapter explicitly addresses the question of capacity constraints between systematic and discretionary CTAs. Could the differences between these two types of funds affect the response of their returns to capital inflows? I hypothesize that, if at all, and despite the fact that futures markets are relatively liquid and deep, discretionary funds are more likely than systematic funds to experience capacity constraints. This is due to the fact that systematic CTAs are more likely to benefit from diversification across multiple markets whilst discretionary CTAs are limited by the number of markets a human is able to follow. Baltas and Kosowski (2012) recently find a lack of capacity constraints in momentum strategies. They do not, however, use the same data classification as in this study and thus do not examine differences between systematic and discretionary CTAs. Furthermore, if capacity constraints are not the cause of the lack of short-term performance persistence for systematic CTAs this poses an interesting avenue for future research.

3.2 Data

In this study, CTA performance and flows are evaluated using monthly net-of-fee returns and assets-under-management (AUM) of live and dead CTAs reported in the BarclayHedge database between January 1994 and December 2010. This time period spans the bull periods, pre 2000 and 2003-2007, as well as the bear market periods starting with the burst of the technology bubble in the spring of 2000 and the recent financial crisis of 2008. The BarclayHedge database has perhaps the most comprehensive coverage of the total CTAs in existence including the largest percentage of defunct funds (Joenvaara et al. (2012)), thus making it potentially less affected by survivorship bias. Joenvaara et al. (2012) further observe that AUM coverage in the BarclayHedge database is superior to other databases. Since AUM series is especially important for calculating the flow rates, this makes this database particularly attractive.

BarclayHedge reports two separate databases, consisting of both active live and defunct funds, the "graveyard". The graveyard keeps track of the funds that ceased to report to the database because of liquidation or some other reason. To minimize the survivorship bias this study includes both live and defunct CTA funds. For each individual fund, BarclayHedge provides information on monthly returns (net of management and performance fees), assets under management (AUM), management and incentive fees, lockup period, strategy classification as well as brief strategy description and various other information specific to fund characteristics. As of December 2010 there were a total of 4,048 defunct and live CTAs. To avoid double counting, all fund of funds were removed, leaving a total of 3916 unique CTAs with a total AUM at the end of 2010 of about US$480 billion. The industry coverage is shown in Figure 3.1. The assets under management have grown from just over US$20 billion in 1993 to over US$480 billion by the end of 2010. One important item worth noting is the reversal in the growth of the number of CTAs after 2008, the year of the financial crisis. However, this fall in the number of funds was accompanied by a rise in assets under management. Some funds have clearly liquidated but the remaining funds have received more capital, perhaps as investors began to reallocate to the CTAs in the knowledge of their attractive performance during down markets.

In this dataset I control for a number of potential biases. Firstly, I eliminate duplicate share classes from the same fund family. For example two funds can appear in the database under the same name and be run by the same fund manager but one will be denoted as "onshore" and the other as "offshore". These are created for regulatory reasons but are virtually identical to one another. Similarly there can be one fund that is an "LP" and another "Ltd", or "Client" and "Proprietary". There are also many instances of funds that provide multiple share classes denominated in various currencies, EUR or GBP, designed for clients who choose to invest in currencies other than US$. These structures are common in the hedge fund and CTA industries, where managers set up a master-feeder fund structure, with multiple feeders feeding to the same fund. Another example of duplicate funds is when a fund appears with the same name twice but one is an older version designated as "Old". Such a fund will have an identical but shorter return history and should therefore be removed. In order to deal with the duplicates I used the following methodology: firstly I identified all the management companies with multiple funds and searched for funds with the same name by string comparison. Thereafter, if their return series had a correlation of 0.95 or more then they were confirmed as duplicates. To decide which duplicates to remove I used either the longest return series or, if the duplicates had an identical length of return series, I selected the fund with the larger assets under management base. This method is similar to the one employed by Aggarwal and Jorion (2010) and Avramov et al. (2011). It is important to emphasize that this procedure would understate the aggregate assets for the manager of the fund with the duplicates that exist side by side with their own respective AUM. However, this is not crucial for the remainder of the analysis but for the purposes of accuracy, Figure 3.1 shows total assets in the industry by including all the duplicate funds.

Apart from removing duplicates I also removed funds that reported gross-of-fee returns and funds that reported quarterly returns instead of monthly returns. As a result, the remaining dataset of CTAs contained 2677 funds, of which 728 funds were in the Live database and 1949 funds in the Defunct database. Furthermore, I removed funds that had no AUM series but only a return series and applied the dynamic AUM filter used throughout this study. This left a total of 908 funds. There were further concerns on the accuracy of the information on total assets-under-management (AUM), since for some funds reported values ended in substantial number of zeros. Because money flows will be derived from the reported AUM values, these zeros had to be removed. If a fund had one month of missing assets under management, I linearly interpolated the missing observations using adjacent assets under management. If assets under management were reported as 0 in the middle of an AUM series, those observations were eliminated and the longest resulting AUM time-interval was reported. Because this study uses quarterly data as well as yearly data, all the funds with less than four quarters of return history were also removed. Although this may impose a survival condition, it also insures that a sufficient number of lagged returns would be available for model estimation. Furthermore, it removes the extreme cash inflow rates that are commonly associated with the incubation stage (Baquero and Verbeek, 2009). Finally, after these extensive filters, there were 854 funds left in my sample.

3.2.1 Share Restrictions

In contrast to the study of Ding et al. (2009), who report various parameters for share restrictions obtained from the TASS database, this study is unable to collect this data due to incomplete information in the BarclayHedge database. Out of 2677 funds, this information is frequently missing or simply written as "Not Provided". For example, for advance notice period, out of 2677 funds 1231 funds have this field empty. Ding et al. (2009) show that asset illiquidity and the smoothing parameter, θ_0, can be used as a proxy for share restrictions. Although there is a distinction at the fund level and asset illiquidity at the underlying security the authors demonstrate that all the restrictions such as subscription, redemption, advance notice and lock-up periods increase monotomically with an increase in asset illiquidity. This study will therefore use the asset illiquidity parameter, θ_0 to model share restrictions.

3.3 Methodology

3.3.1 Capital Flow Analysis

An important characteristic of this study is the use of quarterly data as well as annual data. Since CTAs are reported to be more liquid than hedge funds the use of quarterly data is particularly important as it enables an exploration of the short-term dynamics of the inflows and outflows. Previous studies have mainly used either annual data, e.g. Agarwal, Daniel and Naik (2009), Ding et al. (2009). Others have employed quarterly time horizon, Getmansky (2005), Fung et al. (2008) and Baquero and Verbeek (2009).

Following Sirri and Tufano (1998) and others, flows are measured as the growth rate of a fund's total assets-under-management (AUM) between the beginning and end of the quarter t, net of investment returns, assuming all the dividends are reinvested. The definition assumes that flows occur at the end of the period t.

$$Flow_{i,t} = \frac{AUM +_{i,t} - AUM_{i,t-1}(1 + R_{i,t})}{AUM_{i,t-1}} \tag{3.1}$$

Baquero and Verbeek (2009) also use an alternative measure, DollarFlow:

$$DollarFlow_{i,t} = AUM +_{i,t} - AUM_{i,t-1}(1 + R_{i,t}) \tag{3.2}$$

This definition has a drawback in the event that inflows or outflows are proportional to the size of the fund, irrespective of its performance. On the other hand, the other measure of flow can be magnified by the inflow rates of small funds. Since this study has removed small funds this is unlikely to be a problem and therefore the first definition is used throughout this study. The flows are winsorized at the 1st and 99th percentiles to prevent outliers from affecting the analysis.

3.3.2 Performance Measures and Flow-Performance Relationship

The flow-performance relationship requires the use of the right performance measure. From a theoretical perspective I use the information that would be available to prospective investors: i.e. simple performance measures that are available in most databases, raw returns. Baquero and Verbeek (2009) show that relative performance is also a good predictor of flows as well as absolute performance. Following previous literature, I use relative performance.

In order to study the differential response of flows to past performance I use the methodology of Sirri and Tufano (1998), also used in the hedge fund literature, by using a piecewise linear regression. To that end, each year, I separate fund returns in the cross section into performance terciles. To do this as in Sirri and Tufano (1998) I first assign to each fund i a fractional rank, $Frank_{i,t-1}$, from 0 to 1 which is based on returns during previous year/quarter. This fractional rank represents the fund's percentile performance relative to other funds with the same investment objective in the same period. For example if a fund has a $Frank_{i,t-1}$ of 0.20 this means that the fund was better than 20% of its peer group. In this study, fractional ranks are defined on the basis of funds' raw returns. I then estimate the coefficients on fractional ranks using piecewise linear regression over three terciles that allows one to estimate a possible differential response of money flows to past performance. Sirri and Tufano (1998) and Agarwal et al. (2003) use quintiles instead of terciles but then group the middle three quintiles together as they find that the coefficients on the middle three quintiles are not significantly different from each other. Therefore, following Getmansky (2005) and Ding et al. (2009) I use terciles to estimate piecewise linear regression. Towards that end I define $Trank_{i,t}$ as:

$$\begin{aligned}
Trank^1_{i,t} &= MIN(\frac{1}{3}, Frank_{i,t}) && \textit{Bottom tercile rank}\\
Trank^2_{i,t} &= MIN(\frac{1}{3}, Frank_{i,t} - Trank^1_{i,t}) && \textit{Middle tercile rank}\\
Trank^3_{i,t} &= MIN(\frac{1}{3}, Frank_{i,t} - Trank^1_{i,t} - Trank^2_{i,t}) && \textit{Top tercile rank} \quad (3.3)
\end{aligned}$$

For example if a fund's fractional rank in the previous year/quarter was 0.4 then it would have bottom tercile rank, $Trank^1_{i,t} = Min(\frac{1}{3}, 0.4) = \frac{1}{3}$, middle tercile rank, $Trank^2_{i,t} = Min(\frac{1}{3}, 0.4 - \frac{1}{3}) = 0.07$ and top tercile rank equal to $Trank^3_{i,t} = Min(\frac{1}{3}, 0.4 - \frac{1}{3} - 0.07) = 0$. The coefficients on these piecewise decompositions of fractional ranks i.e. Tranks, represent the slope of the flow-performance relationship over different performance regions and thus capture incremental slope coefficient with respect to the previous performance region. In such specification therefore, concavity in the flow-performance relationship is represented by the slope coefficient of the bottom Trank being significantly higher than the next Trank whilst the convexity is represented by the slope coefficient of a higher tercile being higher than the previous lower tercile.

In order to compare my findings for CTAs with those of Ding et al. (2009), Agarwal et al. (2004), Baquero and Verbeek (2009) for hedge funds and Sirri and Tufano (1998) for mutual funds, I follow a similar methodology and use the following multivariate regression to examine the determinants of money flows into CTAs.

$$\begin{aligned}
Flow_{i,t} &= \alpha_i + \sum_{j=1}^{3} \beta^j_1 Trank^j_{i,t-1} + \beta_2 \sigma_{i,t-1} + \beta_3 ln(AUM_{i,t-1}) + \beta_4 ln(AGE_{i,t-1}) + \\
&\quad + \beta_5 Flow_{i,t-1} + \beta_6 Live_i + \beta_7 HWM_i + \beta_8 ManagementFee_i + \\
&\quad + \beta_9 IncentiveFee_i + \beta_{10} StyleEffect + \epsilon_{i,t} \qquad (3.4)
\end{aligned}$$

where $Trank^j_{i,t-1}$ is as defined before, $\sigma_{i,t-1}$ is the standard deviation of monthly returns of fund i during quarter/year *t-1*. Included are also the natural logarithm of size and age of fund i in the previous period. Unlike Ding et al. (2009), I include the logarithm of age and size to account for the possible nonlinearity. $Flow_{i,t-1}$ is the money-flow in fund i in the previous quarter/year, $Live_i$ equals 1 if the fund is in the Live database, and 0 if it is in the Defunct database, HWM_i equals 1 if a fund has a high water mark provision and 0 otherwise, $ManagementFee_i$ is the management fee charged by the fund and measured as a percentage of assets under management, $IncentiveFee_i$ is the incentive fee charged by fund i, also measured as a percentage of a fund's upside. Style Effect captures the influence of average flow into the same style as the fund i, and $\epsilon_{i,t}$ is the error term.

Hypothesis 1: Positive fund flow-performance relationship: Funds with better past performance will attract higher inflows than funds with lower performance

As discussed before, it is likely that good past performance will serve as a signal to investors and will attract new inflows. As CTAs are restricted from advertising, investors will infer manager's ability from past performance. That is the relationship will be positive. However, given the results of the mutual fund and hedge fund literature, this relationship may not be linear - that is the response of investors to past performance may be differential depending on the fund's past relative performance.

Hypothesis 2: Funds with higher past inflows are likely to attract higher current flows

In addition to past performance, investors may also use past flows as a signal of manager's ability, that is higher past inflows into a fund will signal a manager's quality. Previous studies in the hedge fund literature have found a positive and significant relationship between past and current flows, Agarwal, Daniel and Naik (2004) and Getmansky (2005).

Hypothesis 3: Size of the fund is likely to negatively influence future inflows

Previous literature on hedge funds has found that larger funds are less likely to receive future inflows, Getmansky (2005), Agarwal et al. (2004) and Ding et al. (2009). Ding et al. (2009) show that percentage flows are less sensitive to performance for larger funds indicating that these funds are too large to efficiently exploit market inefficiencies. A priori it is unclear as to the direction of this relationship for CTAs as the main trading style of many CTAs is trend-following.

In analyzing the above relationship, I estimate each quarter or year a piecewise linear regression using Fama and Macbeth's (1973) technique. Cross-sectional regressions are run each quarter/year. Thereafter, the time-series of the estimated coefficients are averaged and their t-statistics are computed. Following Petersen (2009), t-statistics are scaled to adjust for the possible correlation in coefficients across time. As argued by Sirri and Tufano (1998) this multivariate regression can be estimated using a pooled regression method as well as Fama and MacBeth (1973) procedure. However, the authors highlight the potential problems in using a pooled regression technique, which implicitly assumes each fund-quarter/year observation to be an independent observation. If this assumption is violated, it will lead to an underestimation of the standard errors and hence the statistical tests will be inaccurate. Therefore, Sirri and Tufano (1998) recommend the use of the Fama and MacBeth (1973) technique which produces more conservative estimates of the standard errors. For this reason, this technique has also been adopted in the previously mentioned studies of the flow-performance relationship e.g. Ding et al. (2009), Getmansky (2005) and Agarwal et al. (2004).

3.3.3 Asset Illiquidity Parameter, θ_0

Getmansky, Lo and Makarov (2004) propose a general model of the illiquidity and smoothing of hedge fund returns. Denoting the true economic return of a hedge fund in period t by R_t, R_t is then assumed to satisfy the following linear single-factor model:

$$R_t = \mu + \beta\Lambda_t + \epsilon_t, \quad E[\Lambda_t] = E[\epsilon_t] = 0, \quad \epsilon_t, \Lambda_t \sim IID \tag{3.5}$$

and

$$Var[R_t] \equiv \sigma^2 \tag{3.6}$$

This true return represents the return that would determine the equilibrium value of the fund's securities in a frictionless market. This true return is rarely observed, however, and instead we observe R_t^0 which represents the reported return in period t. The authors model this return as:

$$R_t^0 = \theta_0 R_t + \theta_1 R_{t-1} + \theta_2 R_{t-2}$$
$$\theta_j \in [0,1], j = 0,1,2$$
$$\theta_0 + \theta_1 + \theta_K = 1 \tag{3.7}$$

R_t^0 is a weighted average of the fund's true monthly returns, R_t, over the most recent k+1 months including the current months. Getmansky, Lo and Makarov (2004) set k to 2 and estimate θ_0, θ_1, θ_2 using a maximum likelihood procedure. As such, θ_0 measures asset illiquidity or return smoothing. If θ_0 is close to 1 for a specific fund then most of the real contemporaneous return is currently reflected in the observed return, therefore such a fund exhibits lack of smoothing and more liquidity. If θ_0 is small, however, then a fund is rather illiquid and is more likely to exhibit smoothing of returns. Getmansky, Lo and Makarov (2004) also impose a five-year filter on the funds' return history in order to obtain more accurate estimates of θ_0, θ_1 and θ_2.

3.3.4 Performance Persistence and Flows

To explore the link between performance persistence and flows, I follow the methodology proposed in Baquero and Verbeek (2009) and sort CTAs each quarter/year into quintile portfolios based on past quarter/year t-statistics of alphas and independently on past quarter/year flows. When estimating alphas I extend the Fung and Hsieh factors with the addition of GSCI in excess of the risk free rate and apply the Bayesian Information Criterion (BIC) to identify the optimal number of factors for each fund. This procedure amounts to picking the right combination/number of factors by essentially maximising the adjusted-R^2. The actual formula is given by:

$$BIC(K) = ln\left(\frac{\mathbf{e'e}}{n}\right) + \frac{Klnn}{n} \tag{3.8}$$

I then construct portfolios at the intersection of flows and t-statistic of alphas. Three middle quintiles are grouped into one portfolio and therefore nine portfolios are formed. These portfolios are formed equally-weighted as well as flow-weighted and their returns in the subsequent quarter/year are analyzed.

3.3.5 Smart Money Effect

To measure the performance of flows I use a portfolio sorts approach rather than a regressional approach. In particular, two methodologies proposed in the literature are employed. Firstly, I follow Zheng (1999) and apply a measure of portfolio performance first introduced by Grinblatt and Titman (1999), the GT measure, defined as:

$$GT_{t+1} = \sum_{t=1}^{N} (w_{i,t} - w_{i,t-1}) R_{i,t+1} \tag{3.9}$$

where $w_{i,t}$ and $w_{i,t-1}$ are the weights of CTA i at the end of quarters t and *t-1* as measured by assets relative to the total assets of the CTA industry. $R_{i,t+1}$ is the raw return of fund i between time t and *t+1*. N denotes the total number of CTAs used in the sample. This expression represents the return to the dollar invested in a zero-cost portfolio. As shown in Zheng (1999), under the null hypothesis that investors have no selection ability the expression above would converge to zero in large samples[3]. Alternatively, if the investors are smart in allocating their capital to future well-performing funds then the average GT measure over the sample period used should be significantly positive and converge to the covariance, under the assumption that the weights are uncorrelated to the raw return, $R_{i,t+1}$.[4] The advantage of this measure is that it exclusively measures the selection ability of investors and does not require a knowledge of the benchmark, which is particularly useful to the study of CTAs and hedge funds. The authors who have applied this measure are Zheng (1999) and Ding et al. (2009).

As well as applying the GT measure, Ding et al. (2009) create two zero cost portfo-

[3] See Grinblatt and Titman (1993) for a full discussion of the measure.
[4] See Zheng (1999).

lios, equally and flow weighted, to measure the existence of smart money. Specifically, at the beginning of each quarter, each fund is put into either a positive-flow or negative-flow portfolio depending upon whether the flows in the previous quarter were positive or negative. The portfolios are formed by going long on the positive flow funds and going short on the negative-flow funds and are created either equally-weighted or flow-weighted. Portfolios are re-balanced quarterly and held for a quarter. Although this is not an implementable trading strategy as currently there is no secondary market for tradable CTAs and hence one can not short a CTA, nevertheless, the strategy serves to show the relationship between flows and performance. The above measures only show the effect of flows on the next period return. If the smart money effect holds, however, one should be able to see the difference in performance between the high and low flow portfolios persist for the months following the formation. In this spirit, I follow the methodology of Baquero and Verbeek (2009) and form positive-flows portfolios and negative-flows portfolios by creating two *investment* and *divestment* portfolios. Following Zheng (1999), the performance of these portfolios is examined over several holding periods, from one to eight quarters, by compounding their returns. In addition both equally-weighted and flow-weighed portfolios are formed. The procedure is repeated each quarter with portfolios re-balanced assuming investors adopt the follow-the-money approach. Time average of the time series are reported for the holding periods as well as the ranking period.

3.4 Results

3.4.1 Descriptive Statistics

Table 3.1 shows summary statistics for equally-weighted CTA quarterly flows across each category for the period January 1994 to December 2010. Panel A shows quarterly flows for the entire dataset of all funds, Panel B shows the same statistics for Live funds only and Panel C for Defunct funds. Flows are defined as the percentage change in assets between the end of the previous quarter and the end of the next quarter, net of quarterly returns. Initially, flows are calculated for each CTA for each quarter. Then they are aggregated for each category using equal weights. For each category flows are also winsorized at the top 1% to prevent the influence of outliers. Table 3.3 also shows the quarterly flow rate, return and aggregate AUM for the CTA industry for each quarter over the period January 1994 to December 2010.

Panel A of Table 3.1 shows that the average growth rate of the entire sample was 10.75%. This is slightly lower than the 15.93% rate reported for hedge funds in Ding et al. (2009) but slightly higher than the rate reported there for managed futures. The flow rate is highest for systematic short-term trend-following funds (23.57%) and discretionary technical funds (19.05%). Categories with the lowest flow rates are systematic long-term trend-following funds (4.32%) and medium-term trend-following funds (7.82%). Nevertheless, all these rates are still higher than comparative equally-weighted returns from Table 3.2, which are less than 3%, demonstrating that CTAs grow mainly externally from an increase in client capital inflows. Of interest is the standard deviation of 6.54% which is significantly lower than the standard deviation of hedge funds reported in Ding et al. (2009). For some strategies, however, the volatility of flows is much higher: systematic short-term trend-following funds and discretionary technical and spread/RV funds exhibit volatility of flows of 23.53%, 23.43% and 30.25% respectively. Flows of discretionary funds are overall more volatile than flows of systematic funds. For all CTAs, average flows fluctuate from a minimum of -3.38% to a maximum of 25.68% although these rates are much higher for other strategies e.g. systematic short-term funds with a maximum of 120.94%. All CTAs exhibit positive skewness of flows, with the discretionary spread/RV funds having the most positive skewness of 2.59. Similar to the findings of Ding et al. (2009), flows also appear to be sticky with a serial correlation of 11.43. The Jarque-Bera test of normality is rejected for all funds apart for two substrategies, options and systematic pattern recognition.

Panels B and C show the same statistics for Live and Defunct funds separately. Flows are higher for Live funds, with an average flow rate for all CTAs of 11.06% and

8.71% for Defunct funds. The standard deviation of flows of defunct funds is also higher at 10.22% compared to live funds at 6.25%. Minimum flows are also lower (more negative) for Defunct funds than Live funds (-20.03% compared to -1.07%). Nevertheless, maximum flows are similar between Live and Defunct funds. Flows of Live funds are also more sticky with higher serial correlation, 14.66%, compared to 9.41% for Defunct funds.

Table 3.2 shows descriptive statistics for quarterly returns of CTAs. The most represented style is systematic with 589 funds out of 894 funds. Panel A shows descriptive statistics for all funds together, Live and Defunct, whilst Panels B and C show the same statistics for each group separately. In each panel, statistics are calculated for an equally-weighted portfolio of funds within each category. On average all CTAs exhibit a quarterly return of 2.87% with systematic long-term trend-following funds and discretionary fundamental & technical funds achieving the highest quarterly returns of 3.35% and 3.51% respectively. Options funds and systematic funds have higher standard deviations than other funds, whilst the highest maximum return is achieved by the systematic long-term trend-following funds. The Jarque-Bera normality is rejected for funds engaging in options strategies, which is consistent with these funds engaging in highly leveraged strategies with option like features, Agarwal and Naik (2004). In terms of higher moments, only options funds have negative skewness (-0.39%) whilst the remaining funds have positively skewed returns. Kurtosis appears to be normal for most funds apart from discretionary fundamental and technical funds that have a kurtosis of 7.07.

The average serial autocorrelation is negative at -3.41% but some funds, such as discretionary spread/RV and systematic short-term funds, exhibit high and positive autocorrelation of 10.7% and 10.92% respectively. Consistent with Getmansky, Lo and Makarov (2004), funds that hold and trade illiquid securities tend to have highest first order serial correlation. Discretionary spread/RV funds are similar to Fixed Income Arbitrage funds that have been shown to have high autocorrelation coefficients[5]. The

[5]See Getmansky, Lo and Makarov (2004).

reason for the high autocorrelation coefficient of systematic short-term funds is unclear. Panels B and C show that an equally-weighted portfolio of Live funds has a higher mean quarterly return (3.54%) than Defunct funds (2.43%) consistent with poor performance being the reason for the funds' liquidation. The maximum return is higher for Live funds than for defunct ones (17.16% compared to 12.55%). The autocorrelation coefficient is also less negative for Live funds and more of the Live funds' categories reject the Jarque-Bera normality of returns, indicating that some of the Defunct funds engage in more levered and speculative strategies.

Table 3.3 shows the evolution of returns and flows for each quarter over the entire period. Aggregate Assets-under-Management grew from around US$20000 million to almost US$280000 million. The periods of the highest quarterly returns occurred in the third quarter of 1998, fourth quarter of 2000, second and third quarters of 2002 and around 2008. These coincide with the periods of structural breaks identified in the second chapter and coincide with the major crises in the financial markets: the LTCM debacle of 1998, the 2000 technology bubble crush and the 2008 financial crisis. It is also clear that investors are responsive to returns, as the largest inflows are observed straight after the above mentioned crises and periods of high return. In particular, following two quarters of 10.23% and 7.56% returns in 2002 quarters two and three, the average flows to CTAs increased to 17.35%, 22.61% and continued at a higher than average rate until well into 2004. Similarly, inflows were larger after the 1998 crisis. The first quarter of 2008 saw an increase in quarterly inflows indicating investors reallocating to CTAs during the crisis.

3.4.2 Smoothing Parameter, θ_0

Table 3.4 shows results for asset illiquidity and the smoothing parameter, θ_0, calculated by strategy as well as pulling all CTAs together. Panel B of Table 3.4 shows results by strategy while separating funds into Live and Defunct groups. θ_0 is an asset illiquidity measure as well as the degree of smoothing, as defined in Getmansky et al. (2004). Ding et al. (2009), however, show that it could also be useful in capturing share restrictions employed by hedge funds. Whilst Ding et al. (2009) employ both share restrictions as well as θ_0 to measure how restrictive the funds are, I am unable to use share restrictions due to incomplete information on these parameters in the BarclayHedge database.

To measure the degree of restrictions imposed, θ_0, I follow the methodology of Getmansky et al. (2004) and include only funds with a 5-year return history in the calculation of θ_0. This reduces the sample size to 536 funds compared to 894 previously. Table 3.4 shows that when taking all 536 funds together, the median asset illiquidity proxy, θ_0, is 1.01, which is higher than the 0.86 reported for hedge funds in Ding et al. (2009). If θ_0 for a particular fund is close to 1 then that fund exhibits more liquidity and less return smoothing as most of the contemporaneous return is reflected in the observed data. Getmansky, Lo and Makarov (2004) estimate θ_0 for managed futures for the period 1994 to 2002 at 1.13, which is similar to my results. Of particular interest are the differences in results for systematic and discretionary funds. The median θ_0 for most systematic funds, apart from spread/relative value, is above one at 1.05, which is in line with the high liquidity of the CTA strategies. Discretionary funds on the other hand, have a lower median θ_0 of 0.92 and closer to the 0.86 median θ_0 reported for the entire universe of hedge funds in Ding et al. (2009). This highlights the differences in the trading style between systematic and discretionary funds where discretionary funds are able to engage in any trade that the manager may deem profitable at the time, perhaps at times at the expense of liquidity. Discretionary spread/RV funds in particular, have a median θ_0 of 0.68 which is consistent with these funds being more restrictive and is similar to the figure of 0.76 in Getmansky et al. (2004) for Nondirectional/Relative Value funds, which the authors show to be the ones with the largest serial correlations. Again, systematic spread/RV funds, although more liquid than their discretionary counterparts, still have the lowest median θ_0 out of all systematic funds, 0.93. Nevertheless, it is still makes them more liquid than the average hedge fund.

Panel B of Table 3.4 reports the same statistics across all CTA categories separated by funds having a status of being live or defunct. The last column reports difference in the means of θ_0 between live and defunct funds. Apart from the discretionary technical funds, systematic and discretionary funds have higher θ_0 for defunct funds, indicating that Live funds are perhaps more restrictive, a finding similar to Ding et al. (2009). Apart from systematic pattern recognition, however, none of these differences are statistically significant. In addition, defunct options funds have lower θ_0 than live funds.

Table 3.5 shows whether share restrictions may have an impact on fund return volatility. For each CTA category, funds are separated into those with below median θ_0, called Low θ_0 Funds, and those with above median θ_0, denoted as High θ_0 Funds. For each category, each CTA's observed returns are unsmoothed using Getmansky et al. (2004) econometric model and the volatility of the real returns is calculated. Table 3.5 then reports the average and the median standard deviation of returns and the difference between these averages. High θ_0 funds, or funds with low restrictions, appear always to have higher volatility of returns than funds with greater restrictions. These differences, interestingly, are statistically significant for the entire group of CTAs together. However, once one looks at the sub-strategies it is apparent that the difference is mainly driven by systematic funds and, in particular, by the systematic trend-following funds. The results indicate that investors understand the impact of share restrictions, in particular when funds are more volatile, as the option to redeem becomes more valuable.

3.4.3 The Flow-Performance Relationship of CTAs

This section discusses the dynamics of the relationship between flow rate and past performance in the CTA industry. Table 3.6 shows the results for Fama-MacBeth OLS estimates of the piecewise linear regression as defined in equation (3.4). Current quarterly fund flows are defined as a percentage change between this period and past period assets, adjusted for investment returns. Table 3.6 shows results for quarterly flows in Panel A and yearly data in panel B. Baquero and Verbeek (2009) point out that it is important to model fund flow-performance relationship using quarterly data rather than annual data as in Ding, Germansky, Liang and Wermers (2009) and Goetzmann et al. (2003) which allows to investigate short-term dynamics of flows. In the case of CTAs, most subscription and redemption frequencies are either monthly or at the most quarterly. None are on an annual basis. Therefore, using annual data is less likely to be relevant for CTAs.

Table 3.6 Panel A shows estimates for all CTAs together for low performance (0.201***), middle performance (0.093***) and high performance (0.120**) terciles. Therefore, if a fund was in the top tercile in the last quarter an increase in return by 10% would lead to an increase of 1.2% in flows, while if the fund was in a bottom tercile an increase in return in the last quarter of 10% would lean to an increase of 2.01% in flows in the next quarter. Although the top performing funds appear to be growing not proportionately as much as the average fund in the market, the relationship still appears to be linear. All three estimates are significant and, although they are not identical, the Chow (1960) test does not reject the equality of these coefficients and therefore linearity is not rejected. The relationship for quarterly flows and performance appears to be linear when all funds are taken together. This relationship remains linear for the yearly fund flow relationship, as shown in column two of Panel B, although the high performance estimate is not significantly different from zero. Other significant variables are size, defined as the natural logarithm of the last quarter's assets under management, last quarter's flow, live/defunct variable and the style effect. Past flows have a positive effect on current flows with a significant coefficient of 0.143 for quarterly data but are not significant for the yearly data. Hence, flows persistent only in the short-term and not in the long-run. Ding et al. (2009) also document that standard deviation is a significant variable, but for my CTA data it is only significant for Live funds, as shown in column four of Panel A. Standard deviation is significant for yearly flow-performance relationship, which is similar to the Ding et al. (2009) model. Getmansky (2005), however, uses quarterly data and also finds that standard deviation is not significant at this frequency. The relationship between past size and flow, holding other variables constant, is negative, with a coefficient of -0.023. Investors are less likely, or are less able, to invest if the fund is already very large. In addition Live funds receive on average higher inflows that Defunct funds. Unlike, Ding et al. (2009) I do not find HWM, nor management nor incentive fees to be significant. The coefficient estimate for Style Effect variable is positive and significant at 1%. Same style flows positively impact flows to an individual fund, perhaps mimicking the current investors' preferred style.

Quarterly vs. Yearly CTA Flow-Performance Relationship

Panels A and B of Table 3.6 also show the quarterly and yearly performance flow relationship for Live and Defunct funds after controlling for other fund characteristics. For quarterly data, the relationship between flow and performance for funds in the Live database is concave. The low performance estimate is significant, with a coefficient of 0.201, the middle performance coefficient is 0.036 and not significant and the high performance coefficient is 0.138 and significant. The Chow (1960) test rejects the equality of these coefficients. The low-performance estimate is higher than the high-performance estimate, indicating a concave relationship: that is, low performing funds command a disproportionately higher amount of flows than high performing funds. For Defunct funds, the coefficients for the three performance ranks are 0.149, 0.451 and -0.345 respectively. The coefficients for the middle and high performance are significant at 5%. The low-performance estimate is significantly higher than the high performance estimate, again indicating a concave flow performance relationship, although the Chow (1960) test only weakly rejects linearity. Getmansky (2005) also finds a concave flow-performance relationship using quarterly data, even for most hedge fund strategies including managed futures. Ding et al. (2009) use yearly data and find the relationship to be convex for Defunct funds, concave for funds in the Live database and linear for the entire hedge fund database. Baquero and Verbeek (2009) use quarterly data and test rigorously for non linearities in the data to find that the relationship is strictly linear. For the yearly data, Panel B, the Chow (1960) test does not reject the equality of any of the coefficients indicating that the yearly flow-performance relationship is linear for all CTAs irrespective of whether they are in the Live or Defunct database.

Separating Large and Small Funds

I further look at the potential influence of large funds on the flow-performance relationship. To this end, Table 3.7 shows results of Fama-MacBeth OLS estimates for a group of large funds only, i.e. funds that have reached at least US$250 million under management during their reported return series. Again for all CTAs together the relationship is linear. All the variables that were previously significant remain significant for large funds as well. Table 3.7 also shows the flow-performance relationship for large funds from the Live and Defunct databases. For Live funds, the relationship is concave, funds in the low performance tercile receive larger inflows than funds in the highest performance terciles. The coefficient on low performance is 0.222 and significant at 1% whereas it is insignificant for the high performance tercile. The coefficients for defunct funds are very close to each other, 0.196 for the low performance tercile and 0.136 for the high performance tercile, indicating the linearity of the relationship. Interestingly, management fee is significant and negative for large funds in the live group whereas it is insignificant for all the other groups. This indicates that large funds that charge higher management fees receive less inflows than funds that do not. Management fee appears to be an issue for larger funds in attracting funds, less than the rest of the CTA universe. In unreported tests, I estimate the flow-performance relationship for small funds only and find that the relationship is linear across all three databases, all funds together, Live funds and Defunct databases. Thus the concave quarterly relationship of the Live funds reported in Panel A of table 3.6 is driven primarily by the large CTAs rather than share restrictions as shown in Ding et al. (2009) for hedge funds. It is unlikely that share restrictions will have an effect on the flow-performance relationship of CTAs given the highly liquid nature of these funds.

CTA Flow-Performance Relationship by Strategy

In order to ascertain if there are any strategy effects that could affect the flow-performance relationship Table 3.8 reports the flow-performance relationship for each CTA strategy. Panel A shows Fama-MacBeth OLS estimates for the flow-performance relationship for each CTA strategy by taking Live and Defunct funds together. Unlike the results of Getmansky (2005), who shows that the flow-performance relationship is consistent and concave for all hedge fund strategies, CTA strategies exhibit variations in the flow-performance relationship. Firstly, all three terciles are significant for systematic CTAs and most of its sub-strategies, whilst the explanatory power of the regression is weaker for discretionary CTAs and most of its performance terciles are not significant. I apply the Chow (1960) test to test for equality of coefficients of performance terciles to each strategy. Systematic funds and their subcategory, trend following funds, have a linear relationship, whilst systematic spread/relative value funds have a convex relationship with estimates for low performance, middle performance and high performance terciles at (-0.329***), (0.845**) and (0.119) respectively; that is, well performing funds receive disproportionately larger inflows than poorly performing funds. The situation reverses for the discretionary funds that appear to have a concave flow-performance relationship with coefficients of (0.549***), (0.093) and (-0.113) for low, middle and high performance terciles respectively. Furthermore, whilst the flow-performance relationship is concave for most discretionary funds, it is convex for discretionary spread/relative value funds, similar to systematic spread/relative value funds; that is, funds that exploit arbitrage opportunities receive more inflows from investors if past performance was good: there is more return chasing by investors among these funds. Regarding other control variables the situation is different for each strategy. Whilst last quarter's assets under management are significant for all strategies, past flow and live dummy variables are only significant for systematic CTAs. The economically and statistically significant last quarter's flow estimates indicate persistence in money flows for systematic trend-following CTAs. In particular for systematic trend-following funds, an increase in last quarter's flow by 10% increases next quarter's flow by 1.64%, while for systematic short-term trend-following funds a 10% increase in flows induces an increase of 3.51% in flows next quarter. Interestingly, management fee, which was insignificant in a regression with all CTAs becomes significant for systematic spread/relative value funds and discretionary technical funds. This underscores the heterogeneity of CTA strategies.

Panels B and C show by strategy results by separating the funds into large and small funds. Comparing Panels B and C it becomes apparent that the previously found relationship between performance and flows is driven mainly by large funds. The coefficients on low, middle and high performance terciles remain significant for large funds for systematic CTAs, but become insignificant for small systematic CTAs. Nevertheless, the flow-performance relationship for systematic CTAs remains linear for small funds. For discretionary funds, however, the relationship becomes concave, with performance tercile estimates at (0.723*), (0.100) and (-0.641*) for low, middle and high performance terciles respectively. Thus, the concavity in the flow-performance relationship of discretionary CTAs is largely driven by small funds. Regarding other control variables, it appears that the results of Panel A are mainly driven by the large funds: coefficients on the log of assets under management, last quarter flow and live dummy remain significant for large funds but become insignificant for small funds, even though the sample size of the funds in the small group is significantly larger. The results, therefore, confirm that CTA flows respond to historical relative performance and that this relationship depends on the strategy that the fund pursues: systematic CTAs appear to have a linear quarterly relationship, irrespective of whether the funds are large or small, whereas discretionary CTAs have a concave quarterly flow-performance relationship and this is mainly driven by small funds.

Effect of Restrictions on the Flow-Performance Relationship

Table 3.9 shows the effect of possible share restrictions on the flow-performance relationship as discussed in Ding et al. (2009). I hypothesize that given the deep liquidity of the futures markets in which CTAs trade, not many CTAs are likely to have share restrictions. In fact Table 3.4 showed that CTAs have a much higher median restriction parameter, θ_0, compared to the reported median for hedge funds in Ding et al. (2009) and Getmansky et al. (2004). Therefore it is unlikely that share restrictions will have an impact on the flow-performance relationship of CTAs. Table 3.9 shows the effect of the share restriction parameter by running the model in equation (3.4) with additional interaction terms as in Ding et al.(2009): Low Performance*Low θ_0, Middle Performance*Low θ_0 and High Performance*Low θ_0 where Low θ_0 is a dummy variable that equals 1 if θ_0 is below the median level and 0 otherwise. Panel A shows the results for quarterly data and Panel B for yearly data. In Table 3.9 Panels A and B the coefficients on interaction terms are rarely significant. In particular for yearly data, the coefficient on interaction terms is only weakly significant for systematic funds for the High Performance*Low θ_0, making the relationship possibly concave. This is only significant at 10%, however. For quarterly data, the relationship for systematic funds is convex with the addition of interaction terms, even though the coefficients on interaction terms are not significant. The coefficient on the high performance tercile is positive and significant at (0.205***) while for the low performance tercile it is (0.168***). Thus, in the absence of any share restrictions well-performing funds command larger inflows than worse performing funds. This relationship appears to be driven by systematic trend-following funds. Discretionary funds appear to have a linear relationship with none of the interaction terms being significant. Of interest is the significance of interaction terms for all funds in Panel A. Thus, in the presence of share restrictions for all CTAs, the relationship becomes more linear, with coefficients for low performance, middle performance and high performance becoming (0.164), (0.149) and (0.129). In the absence of share restrictions, the relationship still remains linear. Hence, in conclusion, share restrictions have a limited effect on the flow-performance relationship of CTAs.

3.4.4 Performance Persistence and Flows

Berk and Green's (2004) model predicts that as money flows into well-performing funds from investors chasing good performance, the inflow of new assets will compete away any future performance persistence. While this theoretical model fits well with the empirical findings in the mutual fund industry it has not been well sustained by the empirical findings in the hedge fund industry. Baquero and Verbeek (2009) test for performance persistence and find that in the short-term, at quarterly horizons, money inflows do not hurt performance persistence, due to the slow responsiveness of investors to past performance. This could be due to share restrictions and search costs impeding investors from fast allocation of funds, as is indeed possible in the mutual fund industry. On the other hand, with time, at yearly horizons, money inflows compete away any performance persistence. For poorly performing funds, investors' withdrawals act as a disciplining mechanism on the poorly performing funds and thus there is no persistence of poor performance in the short term but only at yearly horizons.

In the previous section of this thesis, I found that systematic CTAs have more persistence at the annual horizon and less at the quarterly one. I also found that whilst performance persistence of discretionary funds is driven by small funds, result similar to the hedge fund industry, performance persistence of systematic CTAs is mainly driven by large funds. Given this finding, this section studies performance persistence of CTAs together with money flows. Figure 3.2 shows cumulative quarterly flows for systematic and discretionary CTAs. The broken red line shows cumulative flows of systematic CTAs and the solid blue line the cumulative flows of the discretionary funds. Over the January 1994 to December 2010 period the cumulative flows of systematic CTAs have slowly surpassed those of the discretionary funds. There is evidence that investors are aware of the difference in the two types of funds and have directed increasingly more capital towards systematic CTAs. This may also point to a lack of capacity constraints among systematic CTAs as they are more able to accept more capital than the discretionary funds. To study the effect of capital flows on the performance persistence of systematic and discretionary CTAs I sort funds each quarter/year into quintiles based on their past quarter t-statistic of Fung-Hsieh alphas and at the same time independently on past quarterly/yearly flows. I then construct portfolios at the intersection of both sorts. Three middle quintiles are then grouped into one portfolio and hence nine final portfolios are formed. Portfolio returns in the next quarter are created by equally-weighting fund returns. This process is repeated each quarter/year with portfolios re-balanced at each time. The results of this method are summarized in Tables 3.10 for quarterly data and 3.11 for yearly data. Looking at the quarterly results for top performers across strategies shows that they are similar across all strategies apart from options. Top performing funds that receive large inflows subsequently underperform funds that receive the lowest flows or which experience outflows. This is consistent with Berk and Green (2004) model whereby large inflows compete away the performance persistence of the best performing funds. Taking all CTAs together, this difference in under-performance amounts to -3.98% per quarter, which is economically but not statistically significant. Results for all systematic funds and systematic trend-following funds are remarkably similar with an economically significant difference between top performing funds with large inflows and outflows of -3.58%. However, this difference in only significant for systematic trend-following funds. Top performing funds in the systematic trend-following group that receive more inflows, on average, perform worse in the subsequent quarter than funds with outflows (average return is 5.04% and is statistically significant). The options strategy is the only strategy where there is performance persistence among top performing funds at the quarterly horizon although the difference between top performing funds with inflows and outflows is not statistically significant. These results are in stark contrast to those reported in Baquero and Verbeek (2009) for hedge funds, who report the continued performance persistence of top performing funds with large inflows at quarterly horizons. Baquero and Verbeek (2005) attribute this to slow responsiveness of money flows, possibly due to share restrictions or search costs. CTAs, however are much more liquid and it appears that investors quickly deploy capital to well-performing funds: the average flow growth rate for top performing CTAs is 66.54% in Table 3.10

whereas it is 39.51% for hedge funds reported in Baquero and Verbeek (2009). Interestingly, the growth rate of options funds is much lower at 26.57%, perhaps explaining the continued persistence of top performing options funds.

Panel C in Table 3.10 shows the performance of the worst performing funds. Here, results are similar to those of Baquero and Verbeek (2009): funds that receive large positive inflows underperform funds that experience outflows. For all CTAs together this difference amounts to -0.91%, similar in magnitude to the -0.98% reported in Baquero and Verbeek (2009) for hedge funds. As investors rush to withdraw capital, they argue, this action acts as a disciplining mechanism on fund managers who sell the worst performing securities fast. Hence, there is no performance persistence either for the top or the worst performing CTAs at the quarterly horizons. The situation reverses dramatically when one looks at Table 3.11, which depicts yearly performance persistence. Looking at all top performing CTAs together we see that these top performing funds that receive large inflows continue to outperform funds that experience outflows, average return of 31.49% per year, statistically significant). This is contrary to the results of Baquero and Verbeek (2009) that is there is evidence of performance persistence at the yearly level. Looking at the results at the strategy level, we see that this remarkable result is driven by systematic trend-following CTAs that show an economically and statistically significant difference in return of top performing funds with inflows and outflows of 3.19% per year. This is also suggestive of smart money in this category. For discretionary CTAs however, the difference in performance between funds with inflows and outflows is negative and statistically significant at -2.47% per year: that is, yearly performance is also competed away by large inflows into discretionary CTAs, a similar result to the one found in hedge funds. These striking results are possibly indicative of a smart money effect or the lack of capacity constraints for systematic CTAs as well as possible capacity constraints or lack of smart money for discretionary CTAs. Looking at Panel C for the worst performing funds at a yearly horizon, systematic CTAs show performance persistence for these worst performing funds with large inflows, although this difference is not economically or statistically significant and systematic trend-followers further show the under-performance of large inflow funds. Overall, at a yearly horizon, funds in the worst performing quintile that experience outflows outperform those that receive inflows. These results are further summarised in Figures 3.3, which shows quarterly and yearly results for systematic CTAs, and Figure 3.4, which shows the same results for discretionary CTAs. The bars represent the time series of portfolio returns that are reported in Tables 3.10 and 3.11. At yearly horizons top performing CTAs with large inflows significantly outperform those with large outflows for discretionary CTAs, with the largest outperformance reported for top performing funds with the lowest inflows (outflows) at the quarterly horizon.

In the second part of this thesis, I documented that size has an effect on performance persistence. In this section I look at the effect of fund flows in large funds on performance persistence. Table 3.12 shows a summary of the results of quarterly and yearly persistence for each CTA strategy for funds in the largest AUM quintile. For comparison purposes the same results are shown for the smallest AUM quintile in Table 3.13. The results found above remain largely unaffected for the funds in the top quintile. We continue to see the performance persistence at annual horizons for top performing funds with the largest inflows outperforming funds with outflows and, this time, the result holds even for discretionary CTAs. The annual results for top performing funds are also economically larger than those documented for the entire sample, with the largest increase documented for systematic CTAs, 7.95% for systematic funds versus 3.84% per year for systematic funds when we look at large and small funds together. We also see a lack of performance persistence for top performing funds with the largest inflows at quarterly horizons and outperformance of the worst performing funds with inflows by funds with outflows. Looking at results for the smallest funds, we see that there is no performance persistence of top performing funds with large inflows at quarterly horizons but there is performance persistence at annual horizon, but this time this is only evident for systematic CTAs and not discretionary CTAs. These results are also depicted in Figures 3.5 to 3.8. Looking at Figure 3.6, which shows results for yearly data for the largest funds, it can be seen that systematic funds in the top performance quintile with large inflows have significantly and economically outperformed funds with the lowest flows. For discretionary CTAs this difference is not very significant. Thus, large top performing systematic funds continue to benefit from inflows. Size and inflows possibly help in research and development of further systematic models. Figure 3.8 shows results for yearly data for the smallest funds. Again inflows do not appear to hinder performance persistence of the top performing funds but at a yearly horizon there is no performance persistence for well-performing discretionary CTAs with large inflows.

3.4.5 Smart Money

This section addresses the smart money effect in the CTA industry. If some funds have superior performance, as measured by both their raw as well as risk-adjusted returns, and investors are able to infer this superiority, then rational investors are likely to allocate more capital towards funds with higher expected alpha. The high flow funds would then have higher returns even though the actual return may not necessarily be affected by flows. Existing literature on smart money is rather mixed. In the mutual fund industry, Zheng (1999) and Gruber (1996) show the existence of smart money: investors are able to select funds by moving away from badly performing funds towards well-performing funds. In fact, the authors find that both raw returns and risk-adjusted returns are significantly higher for funds that experience high inflows. In the hedge fund industry, however, the evidence on smart money is rather mixed and for CTAs it is almost non-existent. Baquero and Verbeek (2009) examine the relationship between flows and returns for hedge funds and find no differences in performance between funds with positive and negative money flows. Ding, Getmansky, Liang and Wermers (2009), on the other hand, find evidence of smart money but only for funds that are not affected by share restrictions. Do, Faff, Lajbcygier and Veeraraghavan (2010) find no evidence of smart money in the CTA industry; they show that chasing past performance does not work, especially in the short-run. This section reports results for the smart money effect for CTA funds and various sub-strategies thereof.

Table 3.14 reports time-series averages across all quarters for the Grinblatt and Titman measure, GT, as well as for the equally-weighted and flow-weighted zero-cost portfolios. The zero-cost portfolios are formed by going long on funds with positive last quarter inflows and shorting funds with previous quarter outflows. These portfolios are then either equally-weighted or flow-weighted across the funds and re-balanced each quarter. If investors have fund picking ability, then the returns of the GT measure and zero-cost portfolios should be positive and significant. Table 3.14 shows that, in fact, none of the measures are positive and significant. For all CTAs together, the GT measure is negative and insignificantly different from 0 at -0.01% per quarter. The only significant GT measure is for systematic spread/relative value funds but it is negative rather than positive: -0.13% for GT measure and -0.89% per quarter for the equally-weighted zero-cost portfolio. Although a few of the returns for the flow-weighted zero-cost portfolio are positive, e.g. long-term trend-following systematic funds have an average quarterly return of 1.01% and discretionary funds 0.08%, none of them are statistically significant. Moreover, the returns to the flow-weighted zero-cost portfolio are not statistically significant for any of the strategies and, for many systematic funds, they are in fact negative. Equally, none of the returns for an equally-weighted zero-cost portfolio are significant, in particular, for all the trend-following systematic funds (i.e. short-term, medium-term and long-term trend-followers) they are negative and insignificant, indicating that funds with inflows subsequently perform less well than funds with outflows and that investors are not able to allocate to future high performers or withdraw money from future losers. The results of this table for CTAs are in stark contrast to the results of Ding, Getmansky, Liang and Wermers (2009) for hedge funds, who find a positive GT measure for all hedge fund strategies other than managed futures. In regard to managed futures, Ding et al. (2009) find that all three measures are negative for managed futures funds, albeit none are significantly negative. Their results thus support the results found here. Do, Faff, Lajbcygier and Veeraraghavan (2010) also find no evidence for smart money in the CTA industry using a regression approach, and show that investors are not successful when chasing past performance among CTAs. By breaking CTAs into sub-strategies my results show that the lack of smart money is driven by the systematic CTAs as the GT measure for discretionary funds tends to be positive rather than negative.

Whilst the results of Ding et al. (2009) show the existence of smart money in the hedge fund industry, they demonstrate that this is only prevalent among more liquid funds as proxied by above median θ_0. By separating funds into those with above median θ_0 and those with below median θ_0, they are able to show that the smart money effect exists only for the most liquid funds. This result, however, contradicts the lack of smart money found both in this study in respect to CTAs and in their study, in that CTAs are among the most liquid funds among hedge funds. In order to see if perhaps smart money effect exists among funds with the highest flows rather than positive flows only, I follow the methodology of Ozik and Sadka (2010). Each quarter, all the CTAs are sorted into three equal-size portfolios based on their prior flow. The portfolios are then re-balanced quarterly and held for one quarter. Thus portfolio one would contain funds with the lowest flows in the last quarter whilst portfolio three would contain funds with the highest flows in the last quarter. If smart money effect is present then portfolio returns should increase with prior flow. For hedge funds, Ozik and Sadka (2010) are able to show that the portfolio return spread of the high-minus-low flow earns 21 basis point per month (2.53% annually) and is statistically significant, thus demonstrating the existence of smart money in the hedge fund industry. Even the Fung-Hsieh alpha of the spread is statistically significant. Table 3.15 Panel A shows excess return, in excess of three-month treasury bills, for CTA portfolios sorted on flows and Panel B shows Fung-Hsieh alphas. For all CTAs together the spread between the highest flow funds and the lowest flow funds is negative and significant, -0.34%. Interestingly, this negative spread is more driven by discretionary funds than systematic funds. Medium-term and long-term trend-followers, in fact, have small positive spreads, albeit non-significant. The spread of the systematic spread/relative value funds is negative and significant suggesting that funds with the highest flows are subsequently less able to earn high returns and in fact under-perform funds with the lowest flow. This effect is most pronounced for spread/relative value funds, since the strategy of these funds requires availability of arbitrage opportunities which may be quickly exhausted with large inflows. The spread for discretionary spread/relative values funds is also negative although weakly significant.

Panel B reports the risk adjusted-returns for (alphas) using the Fung and Hsieh factors augmented with the additional GSCI factor and using the BIC criterion to estimate the alphas.[6] The results from Panel B are similar to Panel A, indicating that the results are robust to risk-adjustment. Again the only strategy to have a significant spread return, albeit negative, is systematic spread/RV.

Long-Run Performance of Flows

Although there is no smart money effect for CTAs in the short-run, it is also interesting to study the long-run performance of the flow strategies. Frazzini and Lamont (2008) look at the long-run performance of the flow strategies of mutual funds and show that the smart money effect disappears in the long-run. Ozik and Sadka (2010) also look at the long-run effect of smart money on hedge funds and find the effect to be permanent, with reversals in performance only occurring for inflows. Ahoniemi and Jylha (2011) find that the out-performance of the high flow is mainly contemporaneous and exists predominantly during the month that the flow occurs and for one month after. Subsequently it completely reverses, indicating a lack of persistence, and thus there is no evidence of a long-term smart money effect. Baquero and Verbeek (2009), on the other hand, find no evidence of flow related out-performance, even in the short-run, thus indicating a complete absence of smart money for hedge funds at the aggregate level.

Table 3.16 shows results that test for the long-run effect of smart money in the CTA universe. It shows the returns of the investment and divestment portfolios in the ranking and post formation periods. Following Zheng (1996), the returns of positive flow portfolios and negative flow portfolios are examined by compounding the returns

[6] The BIC is the Bayesian Information Criterion measure that allows us to choose a subset of factors that achieve the highest adjusted-R^2. It was also employed in the second part of this thesis and was shown to produce superior results.

over different holding periods, from one to eight quarters after ranking. These time series are then averaged. Both equally and cash-flow weighted returns are reported for the investment, divestment and the difference between the investment and divestment portfolios. Table 3.16 reports the results by grouping all the CTAs together, whilst Table 3.17 reports the results of the difference in return between investment and divestment portfolios for each sub-strategy of CTAs. Panel A shows results for investment portfolio for all funds. In the ranking period, the cash-flow weighted portfolio return is significantly higher than the return of the equally-weighted portfolio, with a difference of 1.29% per quarter. This portfolio, however, then underperforms the equally-weighted portfolio in the evaluation periods by -0.06% in the next quarter and -0.1% thereafter, indicating that investors fail to allocate appropriately to the funds that perform best in the following period. The returns for the equally-weighted portfolio increase each quarter but for cash-flow weighted portfolio they decrease with time. These results are similar to those reported by Baquero and Verbeek (2009) for hedge funds. The returns of the divestment portfolio, shown in Panel B, show that investors are able to exploit the liquidity of CTAs by removing money from the funds that subsequently become worse performers, with the returns of the cash flow-weighted portfolio being lower than the returns of the equally-weighted portfolio. Figure 3.9 shows the time-series returns of the investment and divestment strategies for all CTAs. The cash flow-weighted portfolio consistently underperforms the equally-weighted portfolio subsequent to the formation period, a result similar to that of Baquero and Verbeek (2009), although the differences between the two portfolios are substantially larger.

Finally, Panel C compares the investment and divestment portfolio for all CTAs. In the ranking period only the cash flow-weighted portfolio has a sorting capacity. The return to the cash-flow weighted return for the investment portfolio significantly outperforms that of the divestment portfolio. Ozik and Sadka (2011) also find some significant out-performance of the investment portfolio in the ranking period. This out-performance, however, temporarily reverses in the next two quarters and becomes negative, -0.23% for the first quarter and -0.03% for the second, but improves thereafter to return to positive out-performance, although this positive out-performance is not significant. These results confirm the earlier findings on performance persistence in that there is no short-term persistence when sorting on past flows and performance. The results do offer some suggestion of long-term persistence, however, in that there is some evidence in Panel C of the out-performance of the investment portfolio over the divestment portfolio after two quarters. A possible explanation is that the huge inflows attracted by previous high-returns end up being temporarily allocated among less profitable trading strategies resulting in only a temporary reduction in fund returns. Thus, flows appear to have good sorting capacity in the long-term only.

For the equally-weighted portfolio, however, there is no evidence of the investment portfolio outperforming the divestment portfolio. In fact, for equally-weighted return the divestment portfolio marginally outperforms the investment portfolio in both ranking and evaluation periods. Overall, therefore, the results confirm the earlier conclusion that there is no smart money effect at the aggregate level in the CTA industry. Looking at returns of the investment-divestment portfolios for the sub-strategies in Table 3.17 and Figures 3.10 and 3.11 shows that systematic CTAs continue to exhibit temporary underperformance of the investment portfolio relative to the divestment portfolio in the two quarters subsequent to the ranking, with a reversal to a weak smart money effect from the third quarter onwards. This carries across all sub-strategies of systematic funds: short-term trend-followers, medium-term trend-followers, etc. For discretionary CTAs, however, the pattern is reversed: cash flow-weighted returns of the investment portfolio outperform, albeit insignificantly, the returns of the divestment portfolio in the first few quarters subsequent to ranking with a reverse of this outperformance occurring by the 5th quarter. Zheng (1996) also finds the reversal in outperformance for mutual funds and Baquero and Verbeerk (2009) find the same effect for hedge funds. Even though CTAs have reportedly less share restrictions than most hedge funds, however, investors do not always appear to be able to fully exploit that liquidity.

3.4.6 Capacity Constraints

Recent studies in the mutual fund literature have shed light on capacity constraints, Chen et al. (2004) and Yan (2008). Their results provide support for the Berk and Green (2004) equilibrium model that states that in a competitive provision of capital alpha will tend to zero and there should be no performance persistence. In the second part of this thesis I found that, contrary to the earlier findings in the hedge fund literature, alpha has not decreased for systematic CTAs and in particular I found positive and statistically significant alpha in the last period, August 2007 to December 2010. Fung et al. (2008) and Naik, Ramadorai and Stromquist (2007) find that, in the hedge fund industry, fund alpha has declined substantially in the recent period of their study, March 2000 to December 2004. They attribute this decline to the increased capital flows also recorded during this period. Whilst Fung et al. (2008) find capacity constraints for fund of hedge funds, Naik, Ramadorai and Stromquist (2007) look at the capacity constraints at hedge fund strategy level and detect only four out of eight strategies as capacity constrained: Relative Value, Directional Traders, Emerging Markets and Fixed Income. These results indicate that the Berk and Green (2004) model may also hold for hedge funds. Naik, Ramadorai and Stromquist (2007) do not, however, find any capacity constraints for managed futures. In this section, and given the results of this thesis, I directly address the question of capacity constraints at the various levels of CTA sub-strategies with a particular focus on systematic CTAs given the scalability issues of these funds discussed previously. As shown in Figure 3.1, the CTA industry has grown substantially, especially from 2004. This raises the question of whether CTAs may start facing hitherto undetected capacity constraints and, if this is the case, whether this is likely to occur for some CTA strategies more than others.

To the best of my knowledge, this study is the first to examine capacity constraints for various CTA sub-strategies. Would one expect differences in results for various CTA strategies? The fundamental difference between systematic and discretionary CTAs is not the actual strategy, as both are trend-followers, but the way they implement their trading. There is inherently greater potential for scalability for systematic CTAs: once programmed, computers can trade many more markets than a single manager. They may need to be reprogrammed, however, to adjust for inflow of capital. Previously I found yearly but not quarterly performance persistence for systematic CTAs and the reverse for discretionary CTAs. Based on these observations, it is possible to find some capacity constraints for discretionary CTAs as opposed to systematic CTAs.

I analyze the effect of fund flows on CTA performance for each strategy by first computing the returns for each sub-strategy using an AUM-weighted index (henceforth AUMW-index). I further aggregate the flows at the end of each month for each strategy of CTAs, as the AUM-weighted average of individual fund flows.

$$F_s = \frac{\sum_{i=1}^{N_t} AUM_{i,t} Flow_{i,t}}{\sum_{i=1}^{N_t} AUM_{i,t}} \tag{3.10}$$

where $Flow_{i,t}$ denotes individual monthly fund flows, $AUM_{i,t}$ denotes individual monthly fund assets under management and N stands for number of funds in each month in each CTA strategy. Following Naik et al. (2007), I then regress the AUM-weighted return index for each strategy on lagged capital flows and a set of control variables:

$$R_s = const. + \phi \sum_{\tau=t-12}^{t-1} F_s(\tau) + \nu AUM_s(t-12) + \lambda AUM_s^2(t-12) + \chi No.offunds_s(t-12) + \xi_s(t) \tag{3.11}$$

where R_s denotes AUM-weighted strategy return. Also following Naik et al. (2007), I control for size in the CTA industry by including the log of total assets under management in each strategy. To control for potential non-linearity in the relationship, the square of the log of AUM is also included. Naik et al. (2004) also include the number of funds within a strategy in a prior year to control for competition, see Getmansky (2004). A negative and significant value of ϕ is evidence of capacity constraints within a strategy.

Table 3.18 presents the results from estimating the regression given in equation (3.11). The coefficient on lagged flows, ϕ is on average negative but in most cases insignificant. The coefficient is weakly significant for all CTAs taken together and significant at 1% for discretionary and discretionary CTAs that employ technical analysis. This negative and statistically significant coefficient suggests the presence of capacity constraints. That is an increase in 10% in annual flows into these strategies would result in a decrease in subsequent monthly return of 11 basis points for discretionary funds and 15 basis points for discretionary technical funds. Naik et al. (2007) find evidence of capacity constraints for four out of eight hedge fund styles, one of which is Directional Traders. Directional traders are somewhat similar to managed futures in that both can focus on directional trends. Naik et al. (2007) explain the presence of capacity constraints in this strategy if too many directional funds focus on the same sector. Although systematic trend-followers pursue the same type of strategy they do not appear to suffer from capacity constraints. The ability of machines to trade multiple markets simultaneously allows systematic trend-followers to avoid overcrowded trades. A recent Financial Times article observes *"Systematic allows the CTA to trade multiple markets simultaneously."*[7] Thus it appears that discretionary CTAs may suffer from overcrowded trades more than systematic ones. Interestingly, I find that for discretionary and systematic spread/relative value and options strategies the coefficient is positive, although it is not statistically significant. Nevertheless, despite the fact that some of the CTA strategies exhibit a statistically significant ϕ coefficient, it is not economically important just yet. If assets continue to increase at the same rate as in the past few years, however, the effect of flows on returns could become important for discretionary CTAs.[8]

In Table 3.18 the coefficient on size and size squared is only significant for systematic and discretionary spread/relative value funds with reverse signs for the two types of funds. For discretionary spread/relative value funds the sign is consistent with the presence of diminishing returns to scale whereas, for systematic funds spread/RV funds size seems to enhance performance. Competition seems to have no effect on performance in the CTA industry, the coefficient on the number of funds in the strategy is

[7]The Financial Times, June 9, 2012, "A true CTA will stick to chosen path."

[8]An article in the Financial Times on June 11, 2011, states that assets have continued to increase into CTAs despite market downturn.

mostly insignificant. Whilst Do et al. (2010) show that performance has an effect on the timing of funds entering the industry and the overall number of funds, the increase in the number of funds in a strategy does not hinder future performance. This result is contrary to the results of Getmansky (2004) and Naik et al. (2007) who find the effect of competition in the hedge fund industry to be significant. Once again the results are consistent with the evidence that futures markets are relatively deep and liquid.

For robustness, I rerun regression (3.11) using the additional control variables employed in Baltas and Kosowski (2012), S&P 500, Fama-French SMB and HML, Goldman Sachs Commodities Index and Carhart (1997) momentum factor, UMD. Table 3.19 shows the results of this regression. Irrespective of the setup, I find that the results do not qualitatively change: there is no evidence of capacity constraints among systematic CTAs whereas discretionary funds, driven by discretionary technical funds, some show evidence of capacity constraints, confirming previous results.

3.5 Conclusion

In this chapter I analyze the drivers of flows into the CTA industry and their effect on the future performance of CTAs. The nonlinearity of the relationship is modeled with a piecewise linear regression and applied to various CTA categories, fund size and time horizons. I find that at the yearly horizon money flows are linearly related to the past relative performance of the CTAs. At the quarterly horizon, however, this relationship is linear for systematic funds, concave for discretionary funds and convex for spread/relative value strategies across both discretionary and systematic CTAs. This resonates with the earlier results in the literature on hedge funds. Furthermore, unlike the results of Ding et al. (2009), I find no evidence that share restrictions affect the shape of the flow-performance relationship in the CTA industry. Instead, I argue that differences in the relationship can be observed for different fund strategies and fund size. Specifically, the concavity of the relationship is driven by large CTAs, indicating that large better performing funds attract less inflows. Despite the deep liquidity of the futures markets, many large CTAs still choose to close their funds to new investors in order not to hinder future performance. This explains the concavity of the relationship found in this research.

I also examine the effect of flows on the performance persistence of CTAs using quarterly and yearly data. I find no evidence of performance persistence at the quarterly horizon for any of the CTA strategies. However, I find evidence of persistence at the annual horizon. This effect is particularly driven by systematic rather than discretionary CTAs. This resonates with the earlier findings of this thesis that there is yearly but not quarterly performance persistence among systematic CTAs. It appears that this long-term performance persistence is not hindered by the additional inflows of capital and this points to the lack of capacity constraints amongst Systematic CTAs. On the other hand, consistent with the conclusions of Berk and Green (2004), large inflows seem to compete away the performance persistence of Discretionary funds.

This chapter also addresses the issue of smart money in the CTA industry. Despite some evidence of smart money in the hedge fund industry, I find no significant differences in performance between funds with inflows and funds with outflows. Although, in the long-run post formation, there is some reversal in performance of funds with inflows, this out-performance is rather weak. These results are similar to the conclusions of Do, Faff, Lajbcygier and Veeraraghavan (2010). It appears that, despite evidence that CTA investors chase past performance, they are not able fully to exploit it in the short-term. There appears to be no smart money effect in the CTA industry.

Motivated by the above results, I look at the issue of capacity constraints among CTA strategies. My results imply that there are no statistically significant capacity constraints among systematic CTAs but there is statistical evidence of capacity constraints for discretionary CTAs, although it is not yet economically significant. The findings of this study, therefore, have interesting implications for investors. CTAs provide greater liquidity to their investors than hedge funds, thus investors can access many funds relatively quickly, yet it appears that they need to be more patient as to when they choose to exit the funds since performance persistence particularly for systematic CTAs appears to exist only in the long-term after a temporary reversal. The dataset used in this study ends in December 2010, yet assets have continued to flow into the CTA industry. In light of the findings of capacity constraints, investors should consider overall industry flows when investing into discretionary CTAs.

3.6 Appendix

Table 3.1: **Summary Statistics of Quarterly Flows by Category**

Table 3.1 table shows descriptive statistics of quarterly flows for each category of CTAs for the period January 1994 to December 2010 with a minimum of four quarters of quarterly return history. Fund of funds are not included. Panel A shows flow statistics for all funds, Panel B shows statistics for Live funds only and Panel C reports the same statistics for Defunct funds. Flows are computed as the change in total net assets between two consecutive quarters corrected for reinvestments and relative to the assets at the beginning of the period. For each quarter, percentage flows are calculated for each fund which are then equally-weighted across all funds within the respective category. When aggregating the flows, the top 1% are winsorized to prevent the influence of outliers. The table reports equally-weighted mean, median, standard deviation, maximum, minimum, skewness, kurtosis and the first order autocorrelation coefficient of flows. N is the number of funds for each category. The last column reports median Jarque-Bera normality statistics. * is significant at 10%, ** is significant at 5% and *** is significant at 1%.

Panel A: All Funds	**Summary Statistics of CTA Quarterly Flows by Category**									
	N	**Mean** (%)	**Median** (%)	**S.D.** (%)	**Min** (%)	**Max** (%)	**Skew**	**Kurt**	ρ_1(%)	**JB-Stat**
ALL FUNDS	894	10.75	10.11	6.54	-3.38	25.68	0.13	2.39	11.43	23.16***
SYSTEMATIC	589	9.62	8.99	6.92	-7.32	26.78	0.27	2.77	11.88	26.69***
Trend	497	9.26	7.94	6.57	-8.23	24.48	0.22	2.93	12.55	28.07***
Short-term	105	23.57	19.05	23.53	-7.91	120.94	1.43	5.87	14.97	29.46***
Medium-term	309	7.82	7.07	6.59	-8.55	25.20	0.33	3.06	11.15	29.45***
Long-term	83	4.32	3.00	7.08	-10.36	22.03	0.46	2.83	13.09	26.87***
Spread/RV	57	12.94	8.57	18.04	-16.17	83.22	1.08	4.96	9.87	16.70***
Pattern Rec	28	10.08	9.48	18.36	-30.45	67.90	0.92	4.45	6.15	16.92
DISCRETIONARY	267	13.81	13.10	9.40	-5.98	39.25	0.09	2.67	9.05	17.87***
Fundamental	73	9.61	8.74	10.74	-11.62	48.12	0.82	4.72	3.98	13.44***
Technical	85	19.05	13.44	23.43	-15.77	84.89	1.01	3.68	10.96	22.30***
Fundamental & Tech	82	14.64	13.25	13.73	-7.76	67.40	1.27	5.75	9.43	18.17**
Spread/RV	27	12.58	3.59	30.25	-23.31	147.12	2.59	11.24	15.79	10.80***
OPTIONS	38	14.77	12.29	23.59	-37.39	124.51	1.48	8.41	20.61	34.93

Panel B: Live Funds	Summary Statistics of CTA Quarterly Flows by Category									
	N	Mean (%)	Median (%)	S.D. (%)	Min (%)	Max (%)	Skew	Kurt	ρ_1(%)	JB-Stat
ALL FUNDS	358	11.06	12.12	6.25	-1.07	24.66	0.10	2.56	14.66	53.32***
SYSTEMATIC	256	9.74	9.36	6.31	-4.57	25.44	0.26	2.89	15.05	53.86
Trend	221	9.31	9.22	6.24	-5.64	26.02	0.37	3.14	15.28	54.34***
Short-term	59	23.25	15.70	25.85	-13.49	108.82	1.52	5.28	15.83	29.42***
Medium-term	133	7.49	6.46	6.20	-6.71	26.24	0.48	3.42	13.49	64.32***
Long-term	29	4.76	3.49	6.84	-10.46	23.20	0.73	3.25	20.62	82.25***
Spread/RV	21	21.23	11.23	39.98	-31.86	241.49	3.21	15.97	12.36	37.16***
Pattern Rec	12	13.21	4.99	28.26	-36.46	121.38	1.66	6.16	18.13	41.48***
DISCRETIONARY	83	17.64	13.62	19.95	-14.62	105.44	1.66	7.47	8.77	50.23***
Fundamental	30	8.21	6.89	13.70	-14.92	71.25	1.66	8.26	8.28	53.68***
Technical	23	32.36	11.57	81.55	-29.73	598.70	5.14	34.45	0.89	246.75***
Fundamental & Tech	26	17.40	11.08	27.76	-36.49	123.89	1.49	6.42	15.77	20.97
Spread/RV	4	70.24	1.89	215.14	-20.16	758.60	2.91	9.50	25.99	17.80
OPTIONS	19	23.88	13.90	39.45	-5.62	273.21	4.35	26.97	27.80	113.42***

Panel C: Defunct Funds	Summary Statistics of CTA Quarterly Flows by Category									
	N	Mean (%)	Median (%)	S.D. (%)	Min (%)	Max (%)	Skew	Kurt	ρ_1(%)	JB-Stat
ALL FUNDS	536	8.71	8.39	10.22	-20.03	27.18	-0.34	3.23	9.41	13.68***
SYSTEMATIC	333	7.39	7.47	11.79	-24.49	31.76	-0.17	2.93	9.42	14.20***
Trend	276	7.38	7.20	11.77	-27.50	32.10	-0.39	3.49	10.26	18.82***
Short-term	46	20.37	13.87	31.58	-31.76	126.13	1.22	4.52	13.74	33.77***
Medium-term	176	7.36	8.54	10.62	-26.09	31.15	-0.47	3.49	9.26	16.17***
Long-term	54	5.72	2.34	13.25	-20.07	51.66	1.02	4.80	9.39	17.65**
Spread/RV	36	7.16	2.05	20.15	-25.30	82.56	1.05	4.40	8.48	4.49
Pattern Rec	16	8.30	4.88	25.53	-45.08	85.90	0.67	4.09	-3.41	4.67*
DISCRETIONARY	184	11.11	11.50	11.55	-15.79	36.53	-0.07	2.95	9.26	9.80***
Fundamental	43	8.52	5.93	14.26	-15.79	54.77	1.04	4.50	0.97	7.39***
Technical	62	21.19	8.09	52.98	-23.50	384.08	5.08	34.70	14.77	8.70
Fundamental & Tech	56	12.43	10.35	16.10	-19.83	61.80	0.85	3.95	6.17	13.43*
Spread/RV	23	11.32	3.59	30.04	-51.02	139.41	1.81	8.12	14.54	8.52**
OPTIONS	19	8.32	8.66	24.33	-61.99	78.85	-0.13	4.15	12.26	7.24**

Table 3.2: **Summary Statistics of Quarterly Returns by Category**

Table 3.2 shows descriptive statistics of quarterly returns for each category of CTAs for the period January 1994 to December 2010 with a minimum of four quarters of quarterly return history. Fund of funds are not included. Panel A shows flow statistics for all funds, Panel B shows statistics for Live funds only and Panel C reports the same statistics for Defunct funds. Returns are equally weighted for each category. The table reports equally-weighted mean, median, standard deviation, maximum, minimum, skewness, kurtosis and the first order autocorrelation coefficient of returns. N is the number of funds for each category. The last column reports median Jarque-Bera normality statistics. * is significant at 10%, ** is significant at 5% and *** is significant at 1%.

Panel A: All Funds	**Summary Statistics of CTA Quarterly Returns by Category**									
	N	**Mean** (%)	**Median** (%)	**S.D.** (%)	**Min** (%)	**Max** (%)	**Skew**	**Kurt**	ρ_1(%)	**JB-Stat**
ALL FUNDS	894	2.87	2.52	3.59	-5.64	13.77	0.55	3.48	-3.41	1.57**
SYSTEMATIC	589	2.77	2.35	4.59	-7.80	16.55	0.62	3.45	-5.84	1.55
Trend	497	2.82	2.27	4.92	-8.41	17.71	0.65	3.52	-7.09	1.74
Short-term	105	2.64	2.07	2.63	-2.21	11.64	0.70	3.80	10.92	1.52
Medium-term	309	2.79	2.33	5.20	-9.34	17.48	0.59	3.43	-11.50	1.87
Long-term	83	3.35	2.39	7.60	-14.73	25.60	0.63	3.25	-13.46	1.49
Spread/RV	57	2.06	1.67	2.68	-4.07	10.49	0.56	3.48	1.48	1.11
Pattern Rec	28	3.15	2.58	5.53	-8.44	19.12	0.54	3.14	-1.62	0.96
DISCRETIONARY	267	3.07	2.84	2.31	-1.79	9.44	0.56	3.03	1.81	1.41*
Fundamental	73	2.88	2.31	3.50	-3.71	16.63	1.12	5.18	3.25	1.03
Technical	85	3.16	2.88	2.84	-3.94	11.31	0.45	3.38	1.24	1.46
Fundamental & Tech	82	3.51	2.52	3.70	-1.88	18.33	1.80	7.07	-1.80	1.64
Spread/RV	27	2.70	2.55	3.49	-6.21	16.46	0.89	5.80	10.70	1.91
OPTIONS	38	2.99	3.08	4.74	-9.20	14.94	-0.39	3.53	-2.49	6.32*

Panel B: Live Funds	Summary Statistics of CTA Quarterly Returns by Category									
	N	**Mean (%)**	**Median (%)**	**S.D. (%)**	**Min (%)**	**Max (%)**	**Skew**	**Kurt**	**ρ_1(%)**	**JB-Stat**
ALL FUNDS	358	3.54	2.95	4.41	-5.64	17.16	0.75	3.604	-1.43	2.35**
SYSTEMATIC	256	3.51	3.16	5.36	-7.99	21.00	0.81	3.89	-4.81	2.00
Trend	221	3.55	3.13	5.62	-8.44	21.85	0.80	3.84	-6.15	2.52*
Short-term	59	3.22	3.24	3.01	-3.53	11.35	0.36	2.92	12.53	1.79
Medium-term	133	3.50	3.05	5.98	-9.00	22.82	0.76	3.73	-13.68	2.70
Long-term	29	4.11	3.80	8.27	-15.70	26.44	0.55	3.03	-9.60	4.84*
Spread/RV	21	2.83	2.16	4.19	-5.47	15.24	0.54	3.37	-4.39	1.41
Pattern Rec	12	4.08	3.45	8.39	-17.90	27.55	0.32	3.71	18.20	1.97***
DISCRETIONARY	83	3.48	2.75	3.65	-2.46	19.01	1.56	6.82	6.47	2.45*
Fundamental	30	3.32	2.42	5.63	-4.88	23.74	1.41	5.74	3.78	2.09
Technical	23	3.69	2.52	3.92	-1.61	18.68	1.68	6.45	6.95	4.41**
Fundamental & Tech	26	2.75	1.97	4.49	-16.44	13.40	-0.58	6.79	8.19	2.18
Spread/RV	4	4.87	6.04	6.63	-5.95	23.66	0.67	4.09	12.82	1.77
OPTIONS	19	4.54	4.22	6.31	-10.00	17.75	-0.10	3.02	9.59	18.17***

Panel C: Defunct Funds	Summary Statistics of CTA Quarterly Returns by Category									
	N	**Mean (%)**	**Median (%)**	**S.D. (%)**	**Min (%)**	**Max (%)**	**Skew**	**Kurt**	**ρ_1(%)**	**JB-Stat**
ALL FUNDS	536	2.43	2.41	3.41	-5.71	12.55	0.31	3.70	-4.74	1.23
SYSTEMATIC	333	2.04	1.95	4.32	-7.56	14.97	0.48	3.50	-6.63	1.26
Trend	276	2.05	2.01	4.77	-8.37	16.53	0.49	3.61	-7.85	1.38
Short-term	46	2.33	2.60	3.49	-7.91	11.91	0.21	3.98	8.86	1.04
Medium-term	176	2.00	1.91	4.96	-9.81	15.46	0.40	3.33	-9.86	1.43***
Long-term	54	2.47	1.39	7.04	-12.79	26.66	0.94	4.38	-15.54	1.36
Spread/RV	36	1.66	1.50	2.91	-4.18	11.90	0.76	3.92	4.91	0.88
Pattern Rec	16	3.13	3.07	7.68	-16.96	24.48	0.33	3.62	-16.48	0.75
DISCRETIONARY	184	2.99	2.97	2.87	-3.78	11.40	0.57	3.98	-0.29	1.17**
Fundamental	43	2.69	2.18	3.80	-3.78	19.74	1.50	7.44	2.88	0.72
Technical	62	3.10	3.02	3.37	-5.75	12.06	0.29	3.55	-0.88	1.09
Fundamental & Tech	56	3.46	2.72	4.42	-5.30	18.80	1.41	6.17	-6.44	1.38
Spread/RV	23	2.62	2.19	4.15	-7.13	20.63	1.68	9.31	10.34	1.91
OPTIONS	19	2.97	2.86	5.76	-17.44	23.75	0.22	7.02	-14.58	1.26

Table 3.3: **Average Flows, Returns and Aggregate AUM**

Table 3.3 presents shows for each quarter average flow rates, aggregate AUM and average return for the period January 1994 to December 2010. Cash flows are computed as before.

Date	**Number of funds**	**Cash flows (Growth rates %)**	**Aggregate AUM (in US$ millions)**	**Average returns %**
1994Q1	271	21.84	19046.45	-0.28
1994Q2	278	16.91	20202.25	6.57
1994Q3	285	9.57	18806.80	-2.50
1994Q4	293	8.07	18892.71	3.56
1995Q1	291	9.65	19830.09	8.61
1995Q2	304	9.38	19192.82	3.23
1995Q3	306	4.89	18069.99	1.90
1995Q4	300	6.14	19370.33	5.78
1996Q1	302	6.87	18407.61	0.05
1996Q2	312	7.55	18372.20	4.60
1996Q3	307	9.81	18930.65	2.48
1996Q4	306	11.12	20688.31	9.64
1997Q1	302	17.12	21932.03	7.63
1997Q2	309	15.09	23822.50	0.68
1997Q3	308	15.58	26349.25	4.24
1997Q4	312	9.25	26875.68	3.37
1998Q1	315	14.69	28178.16	2.46
1998Q2	328	13.91	28620.90	1.02
1998Q3	333	7.09	33748.79	11.66
1998Q4	328	13.72	33750.41	2.09
1999Q1	326	16.38	35266.35	1.09
1999Q2	338	11.11	37343.23	3.08
1999Q3	343	6.35	37999.67	-0.21
1999Q4	341	4.87	37450.60	-0.95
2000Q1	330	1.59	35275.18	0.67
2000Q2	328	0.05	34193.00	0.49
2000Q3	331	1.79	32210.17	0.24
2000Q4	337	1.58	34818.22	13.77
2001Q1	331	12.63	39443.14	5.15
2001Q2	336	13.60	38929.60	-2.41
2001Q3	335	4.40	43365.25	3.72
2001Q4	338	10.11	44333.67	-0.10
2002Q1	335	12.17	44383.45	-1.83
2002Q2	346	11.19	48211.28	10.23
2002Q3	351	12.87	54320.86	7.56
2002Q4	350	17.35	56187.28	1.06
2003Q1	359	22.61	64344.08	2.52
2003Q2	362	18.79	70549.55	4.96
2003Q3	365	20.87	79867.83	1.49
2003Q4	367	21.77	94078.45	4.45
2004Q1	375	22.37	112102.72	5.82
2004Q2	378	21.04	123782.93	-5.64
2004Q3	393	14.04	127081.28	0.64
2004Q4	410	11.31	140395.86	5.84
2005Q1	410	4.20	125683.37	-1.95
2005Q2	413	3.57	130277.98	2.84
2005Q3	420	11.09	135757.71	2.05
2005Q4	423	13.75	138176.03	3.01
2006Q1	417	15.01	159280.23	2.69
2006Q2	417	19.65	172673.96	2.29
2006Q3	418	10.41	180877.98	-1.02
2006Q4	423	9.87	192134.39	3.87
2007Q1	433	9.37	192705.54	-1.32
2007Q2	433	9.42	207789.78	5.68
2007Q3	428	9.97	214379.30	2.01
2007Q4	424	7.30	225162.41	4.76
2008Q1	420	15.74	258862.63	7.56
2008Q2	421	13.35	280715.79	3.54
2008Q3	418	6.19	263991.17	-1.65
2008Q4	407	-3.38	240124.17	7.91
2009Q1	398	4.90	222745.30	-1.87
2009Q2	384	7.44	224173.48	1.25
2009Q3	373	4.57	238207.31	1.47
2009Q4	361	4.37	242144.48	-0.86
2010Q1	354	0.49	241145.18	-0.22
2010Q2	336	-0.82	244184.11	-0.34
2010Q3	321	1.91	262611.13	4.26
2010Q4	313	1.35	277446.24	4.56

Table 3.4: **Statistics for Restriction Parameter, θ_0**

Table 3.4 reports statistics for the share restriction parameter, θ_0, across all CTA categories for all funds together as well as for Live and Defunct funds separately for the period January 1994 to December 2010. θ_0 is an asset illiquidity measure as well as the degree of smoothing. Following Getmansky, Lo and Makarov (2004), only funds with a 5-year return history are included in the calculation of θ_0 and therefore the sample size in the table below is smaller than in previous analyses. Also reported is the difference in means between live and defunct funds. * is significant at 10%, ** is significant at 5% and *** is significant at 1%. These significance levels are calculated using a two tailed unequal variance (heteroskedastic) test.

	Panel A: All Funds						**Panel B: Live & Defunct Funds**							
							Live Funds			**Defunct Funds**				
	N	**Mean**	**Median**	**Stdev**	**Min**	**Max**	**N**	**Mean**	**Median**	**N**	**Mean**	**Median**	**Diff**	
ALL FUNDS	536	1.05	1.01	0.30	0.44	4.52	255	1.07	1.04	281	1.03	0.98	0.04	0.04
SYSTEMATIC	378	1.07	1.05	0.23	0.51	2.57	192	1.08	1.06	186	1.06	1.03	0.02	0.02
Trend	331	1.08	1.06	0.23	0.51	2.57	171	1.10	1.10	160	1.07	1.03	0.03	0.03
Short-term	61	0.98	0.95	0.21	0.55	1.58	33	1.01	1.03	28	0.94	0.84	0.06	0.06
Medium-term	211	1.09	1.09	0.20	0.51	1.76	113	1.12	1.11	98	1.07	1.03	0.05	0.05*
Long-term	59	1.16	1.08	0.29	0.82	2.57	25	1.12	1.10	34	1.18	1.07	-0.05	-0.05
Spread/RV	27	0.95	0.93	0.19	0.68	1.40	11	0.96	0.93	16	0.95	0.89	0.01	0.01
Pattern Rec	17	1.04	1.01	0.24	0.64	1.65	9	0.95	0.95	8	1.14	1.11	-0.19	-0.19*
DISCRETIONARY	134	0.93	0.92	0.21	0.44	1.85	49	0.95	0.93	85	0.92	0.92	0.03	0.03
Fundamental	40	0.96	0.95	0.14	0.72	1.49	19	1.01	0.99	21	0.92	0.92	0.09	0.09**
Technical	39	0.92	0.89	0.25	0.58	1.85	17	0.85	0.80	22	0.98	0.93	-0.13	-0.13*
Fundamental & Tech	38	0.97	0.94	0.21	0.44	1.55	12	1.00	0.98	26	0.96	0.94	0.04	0.04
Spread/RV	17	0.77	0.68	0.11	0.53	1.02	1	0.82	0.82	16	0.77	0.74	0.05	0.05
OPTIONS	24	1.28	1.06	0.91	0.51	4.52	14	1.28	0.98	10	1.27	1.12	0.01	0.01

Table 3.5: **Restriction Parameter, θ_0, and Return Volatility**

Table 3.5 presents results for unsmoothed/real return volatility for both restricted and unrestricted funds for each of the CTA categories. Unsmoothed returns are obtained following Getmansky, Lo and Makarov (2004) procedure. Following their methodology only funds with 5-year return history are included in the calculation of θ_0 and therefore sample size in the table below is smaller than previous. Restricted funds are defined as those with θ_0 below median level and unrestricted funds are funds with above median θ_0. The difference in means between the two categories is computed. *** is significant at the 1% level, ** is significant at the 5% level and * is significant at 10% level. These significance levels are calculated using a two tailed unequal variance (heteroskedastic) test.

Restriction Parameter and Return Volatility

	High Theta Funds			**Low Theta Funds**			
	N	**Mean**	**Median**	**N**	**Mean**	**Median**	**Diff**
ALL FUNDS	268	4.96	4.02	268	4.38	3.77	0.58*
SYSTEMATIC	189	5.11	4.34	189	4.25	3.69	0.86**
Trend	165	5.32	4.52	166	4.27	3.77	1.05***
Short-term	30	4.22	3.58	31	2.84	2.83	1.38**
Medium-term	105	5.18	4.53	106	4.48	3.68	0.70*
Long-term	29	7.27	6.66	30	4.74	4.67	2.52***
Spread/RV	13	3.86	3.45	14	3.37	3.43	0.49
Pattern Rec	8	4.60	4.47	9	4.65	4.93	-0.05
DISCRETIONARY	67	4.52	2.93	67	4.80	3.99	-0.29
Fundamental	20	4.16	3.19	20	4.79	4.23	-0.63
Technical	19	4.53	2.85	20	4.46	2.89	0.07
Fundamental & Tech	19	5.86	2.93	19	5.74	3.52	0.13
Spread/RV	8	2.54	2.14	9	3.28	3.04	-0.74
OPTIONS	12	5.54	3.75	12	3.53	3.03	2.01

Table 3.6: **Fund Flow-Performance Relationship for All CTAs**

Table 3.6 presents results for Fama-MacBeth OLS estimates with net flow rate as the dependent variable for all CTA funds in the database, as well as by separating all CTAs into those that are live and defunct for the period January 1994 to December 2010. Panel A presents the results for quarterly flow and panel B for yearly flow as the dependent variable. Flows are measured as a growth rate relative to the fund's total net assets in the previous quarter. The independent variables include three terciles of performance in the last quarter/year (Low Performance, Middle Performance and High Performance) as defined in Getmansky (2005). Independent variables accounting for fund specific characteristics include a fund's monthly standard deviation of returns, size (defined as the natural logarithm of a fund's total net assets in the prior quarter or year), the log of a fund's age in months since inception, past quarter/year flow. Live is a dummy variable defined as 1 if the fund is in the Live database and 0 otherwise. HWM is a High Water Mark dummy which is equal to 1 if a high water mark provision is present and 0 otherwise. Management Fee is the fixed fee charged by the fund as a percentage of funds under management and incentive fee is the percentage fee charged by the fund if a fund's upside is above a certain threshold level. Style Effect measures the average flow at time t for a particular category. All standard errors are computed using Newey-West's (1987) method with 2 lags. * is significant at 10%, ** is significant at 5% and *** is significant at 1%.

Panel A: Quarterly Fund Flow-Performance Relationship - All CTAs

	All Funds		**Live Funds**		**Dead Funds**	
Variable	**Estimate**	**t-Stat.**	**Estimate**	**t-Stat.**	**Estimate**	**t-Stat.**
Intercept	0.296***	4.78	0.237***	4.01	-0.429	1.39
Low Performance	0.201***	6.58	0.201***	5.22	0.149	0.83
Middle Performance	0.093***	2.99	0.036	1.18	0.451**	2.63
High Performance	0.120**	2.51	0.138***	2.68	-0.345**	-1.89
Standard Deviation	-0.134	-1.48	-0.243**	-2.45	0.506	0.69
Log (AUM)	-0.023***	-7.09	-0.016***	-5.87	-0.033***	-3.46
Flow	0.143***	8.44	0.143***	8.73	0.133**	2.06
Live	0.039***	5.07				
High Water Mark	0.004	0.59	0.006	1.00	0.026	0.89
Management Fee	-0.115	-0.40	-0.062	-0.15	-1.015*	-1.75
Incentive Fee	-0.014	-0.17	-0.052	-0.6	-0.016	-0.03
Style Effect	0.296***	4.78	0.366***	8.53	0.482***	4.45
Average no. of obs.	894		358		536	
Adjusted-R^2	10.08%		11.45%		8.60%	

Panel B: Yearly Fund Flow-Performance Relationship - All CTAs

	All Funds		**Live Funds**		**Dead Funds**	
Variable	**Estimate**	**t-Stat.**	**Estimate**	**t-Stat.**	**Estimate**	**t-Stat.**
Intercept	4.041***	4.03	3.122***	3.39	1.329	0.26
Low Performance	1.506***	3.83	1.441***	3.63	1.383	1.37
Middle Performance	0.951**	2.13	0.678	1.56	1.164**	2.31
High Performance	0.336	0.50	0.509	0.78	0.244	0.28
Standard Deviation	-2.855***	-3.14	-2.904***	-2.87	-1.037	-0.39
Log (AUM)	-0.249***	-4.27	-0.187***	-3.64	-0.160	-0.64
Flow	0.084	1.48	0.101	1.48	-1.338	-1.00
Live	0.133*	2.03				
High Water Mark	0.018	0.29	0.056	1.01	0.113	0.75
Management Fee	-1.129	-0.44	-1.134	-0.22	-1.178	-0.33
Incentive Fee	-0.097	-0.14	0.132	0.14	0.511	0.50
Style Effect	1.207**	2.76	0.782*	1.87	2.687***	3.75
Average no. of obs.	894		358		536	
Adjusted-R^2	11.70%		8.73%		5.63%	

Table 3.7: **Quarterly Fund Flow-Performance Relationship for All CTAs above US$250 million**

Table 3.7 presents results for Fama-MacBeth OLS estimates with net flow rate as the dependent variable for all CTA funds that had reached at least US$250 million in assets under management for the period January 1994 to December 2010. This table presents results for quarterly data only. Flows are measured as a growth rate relative to the fund's total net assets in the previous quarter. The independent variables include three terciles of performance in the last quarter (Low Performance, Middle Performance and High Performance) as defined in Getmansky (2005). Independent variables accounting for fund specific characteristics include a fund's monthly standard deviation of returns, size (defined as the natural logarithm of a fund's total net assets in the prior quarter), the log of a fund's age in months since inception, past quarter flow. Live is a dummy variable defined as 1 if the fund is in the Live database and 0 otherwise. HWM is a High Water Mark dummy which is equal to 1 if a high water mark provision is present and 0 otherwise. Management Fee is the fixed fee charged by the fund as a percentage of funds under management and incentive fee is the percentage fee charged by the fund if a fund's upside is above a certain threshold level. Style Effect measures the average flow at time t for a particular category. All standard errors are computed using Newey-West's (1987) method with 2 lags. * is significant at 10%, ** is significant at 5% and *** is significant at 1%.

Quarterly Fund Flow-Performance Relationship - All CTAs above US$ 250 million						
	All Funds		**Live Funds**		**Dead Funds**	
Variable	**Estimate**	**t-Stat.**	**Estimate**	**t-Stat.**	**Estimate**	**t-Stat.**
Intercept	0.296***	4.78	0.219***	2.85	0.596***	6.06
Low Performance	0.201***	6.58	0.222***	4.93	0.196***	3.08
Middle Performance	0.093***	2.99	0.087**	2.51	0.077*	1.74
High Performance	0.120**	2.51	0.085	1.29	0.136*	1.72
Standard Deviation	-0.134	-1.48	-0.242	-1.40	0.068	0.46
Log (AUM)	-0.023***	-7.09	-0.018***	-5.17	-0.043***	-7.49
Flow	0.143***	8.44	0.176***	4.95	0.128***	6.40
Live	0.039***	5.07				
High Water Mark	0.004	0.59	0.001	0.15	-0.002	-0.26
Management Fee	-0.115	-0.40	-0.659*	-1.67	0.333	0.79
Incentive Fee	-0.014	-0.17	0.151	1.03	0.085	0.93
Style Effect	0.296***	4.78	0.355***	6.23	0.376***	6.39
Average no. of obs	894		224		670	
Adjusted R^2	10.08%		13.25%		10.21%	

Table 3.8: **CTA Flow-Performance Relationship by Strategy for Large and Small Funds**

Table 3.8 presents results for Fama-MacBeth OLS estimates of the quarterly fund flow-performance relationship by strategy as well as separating funds into large (funds that had reached above median AUM during their lifetime) and small (funds with below median AUM during their lifetime) for the period January 1994 to December 2010. This table presents results for quarterly data only. Flows are measured as a growth rate relative to the fund's total net assets in the previous quarter. The independent variables include three terciles of performance in the last quarter (Low Performance, Middle Performance and High Performance) as defined in Getmansky (2005). Independent variables accounting for fund specific characteristics include a fund's monthly standard deviation of returns, size (defined as the natural logarithm of a fund's total net assets in the prior quarter), the log of a fund's age in months since inception, past quarter flow. Live is a dummy variable defined as 1 if the fund is in the Live database and 0 otherwise. HWM is a High Water Mark dummy which is equal to 1 if a high water mark provision is present and 0 otherwise. Management Fee is the fixed fee charged by the fund as a percentage of funds under management and incentive fee is the percentage fee charged by the fund if a fund's upside is above a certain threshold level. Style Effect measures the average flow at time t for a particular category. All standard errors are computed using Newey-West's (1987) method with 2 lags. * is significant at 10%, ** is significant at 5% and *** is significant at 1%.

Panel A: Fund-Flow Relation by CTA Strategy

	Intercept	Trank1	Trank2	Trank3	S.D.	Log(AUM)	Flow	Live	HWM	Mgmt	Incen.	Style	Obs.	Adj. R^2
SYSTEM.	0.273***	0.169***	0.079***	0.144***	-0.152	-0.021***	0.165	0.043***	-0.001	-0.054	-0.085	0.422***	589	10.29%
TREND	0.302***	0.166***	0.069**	0.158***	-0.159	-0.021***	0.164***	0.040***	0.002	-0.187	-0.115	0.404***	497	9.48%
S-T	0.779***	0.336**	0.166	0.697*	-0.795	-0.045***	0.351**	0.035*	-0.025	-0.98	-0.130		105	6.06%
M-T	0.284***	0.188***	0.048	1.23**	-0.091	-0.020***	0.152***	0.035***	0.005	0.224	0.015		309	6.08%
L-T	0.152	-0.104	-0.423	1.213	0.158	0.004	-0.245	0.022**	-0.102	-2.442	-0.601		83	5.78%
Spread/RV	-0.085	-0.329**	0.845**	0.119	1.551	0.016	-0.029	-0.153*	-0.001	5.524**	-1.882*		57	4.90%
DISCRET.	0.435*	0.549***	0.093	-0.113	-0.672	-0.036***	0.100	-0.005	0.061**	0.111	-0.090	0.528***	267	4.96%
Fundamental	0.653	0.005	0.224	-0.610*	0.791	-0.039	0.219	-0.038	-0.058	-0.627	0.547		73	3.06%
Technical	1.611**	0.240	0.079	0.508**	-0.048	-0.080**	-0.164	-0.023	-0.022	9.503*	-2.075		85	3.36%
Fund & Tech	-0.117	0.235	1.076*	-1.881*	4.113	-0.019	0.275**	0.024	0.339*	-4.778	0.221		82	5.14%
Spread/RV	0.655	-0.119*	0.680	-0.059	-2.247*	-0.036	-0.126	0.062	0.081	-0.631	-0.111		27	1.30%
OPTIONS	0.242	0.511*	0.075	0.013	-0.699	-0.017	0.275***	-0.048	-0.049	2.192	0.021		38	9.46%

Panel B: Fund-Flow Relation by CTA Strategy - Large funds

	Intercept	Trank1	Trank2	Trank3	S.D.	Log(AUM)	Flow	Live	HWM	Mgmt	Incen.	Style	Obs.	Adj. R^2
ALL FUNDS	0.219***	0.222***	0.087**	0.085	-0.242	-0.018***	0.176***	0.037***	0.001	-0.659*	0.151	0.355***	224	13.25%
SYSTEM.	0.229***	0.120**	0.109***	0.116**	-0.311**	-0.017***	0.239***	0.043***	-0.001	-0.741*	0.084	0.407***	167	13.71%
TREND	0.285***	0.084*	0.131***	0.044	-0.366*	-0.020***	0.235***	0.037***	0.001	-0.483	0.246	0.311**	137	10.50%
S-T	0.558*	0.907**	0.089	-0.043*	0.893	-0.043	0.264***	0.068**	-0.019	-1.616	-0.060		9	11.18%
M-T	0.083	0.205**	0.066	0.067	-1.012**	-0.013***	0.192***	0.032**	-0.010	0.384	0.548		81	5.44%
L-T	0.377	-0.045	-0.359	0.211***	0.544	-0.015	0.350**	0.005	0.099	-1.07	-0.09		18	7.77%
Spread/RV	-5.744	-4.524*	-1.229	5.209	1.367	0.197*	-1.019*	-0.931	0.021	-2.052	12.688		22	2.42%
DISCRET.	1.706**	0.329*	-0.005	0.109	0.214	-0.087**	0.120**	-0.149	-0.027	1.4	-0.413	0.344	50	9.67%
Fundamental	0.66	0.503	0.403**	-0.194	-1.807*	-0.038	0.251*	-0.022	-0.060	9.584	-0.721		15	7.69%
Technical	0.560	1.085*	0.253	-0.219	-0.113	-0.024	-0.229	-0.018	0.148	0.487	-1.812		9	3.68%
Fund & Tech	5.215**	2.036*	-2.535	-0.148	-2.489	-0.127	0.608*	-0.073	-0.84	8.526	-1.739		17	2.98%

Panel C: Fund-Flow Relation by CTA Strategy - Small funds

	Intercept	Trank1	Trank2	Trank3	S.D.	Log(AUM)	Flow	Live	HWM	Mgmt	Incen.	Style	Obs.	Adj. R^2
ALL FUNDS	0.596***	0.196***	0.077*	0.136*	0.068	-0.043***	0.128***	0.033***	-0.002	0.333	0.085	0.376	670	10.21%
SYSTEM.	0.540***	0.127*	0.133***	0.066	0.13	-0.039***	0.144***	0.034**	-0.011	0.382	0.008	0.375***	422	9.73%
TREND	0.649***	0.108*	0.058	0.143*	0.019	-0.040***	0.155***	0.029**	-0.01	0.045	-0.228	0.307	360	8.84%
S-T	-3.665	0.875	0.173	-0.596	1.138	0.146**	-0.317	0.319*	0.452	-3.921	3.343		18	4.01%
M-T	0.515***	0.217*	0.173	-0.108	0.699*	-0.035***	0.260*	0.022	0.009	0.372	-0.275		228	5.94%
L-T	0.494***	-0.088*	0.16	0.026	-0.141	-0.031***	0.017	0.050	0.007	3.567	-0.337		65	3.52%
Spread/RV	0.794	0.285	1.285	-0.150	0.028	-0.090**	0.139	0.057***	-0.131	1.750	2.473		58	7.49%
DISCRET.	0.507	0.723*	0.100	-0.641*	1.821*	-0.054**	0.073	-0.026	0.067	1.852	0.421	0.703**	217	5.09%
Fundamental	-0.219	0.398	-0.225	0.444	0.531	-0.056*	0.071	-0.044	0.047	-1.471*	0.37		58	4.05%
Technical	1.039	0.217	0.359	-0.204	-1.815	-0.067	-0.466*	0.051**	-0.108	11.981*	-0.878		76	3.67%
Fund & Tech	0.972*	-0.102	0.105	0.448	-0.133*	-0.062*	-0.017	0.013	0.064	0.714	0.303		65	7.31%
Spread/RV	4.418	-0.485	2.787*	-1.898	-4.866	-0.235	1.714	0.316	0.271	-4.251	-2.779		18	1.82%
OPTIONS	1.074**	-0.247	0.285*	-0.053	-1.070	-0.051**	0.261	0.048	-0.069	-0.696	-0.256		31	11.89%

Table 3.9: **Effect of Share Restrictions on CTA Flow-Performance Relationship by Strategy for Quarterly and Yearly Data**

Table 3.9 Panel A presents Fama-MacBeth OLS estimates of the quarterly fund flow-performance relationship for each CTA strategy for the period January 1994 to December 2010. The restriction, θ_0 is interacted with high, middle and low performance terciles. Low $\theta_0 = 0$ if θ_0 parameter is below median and 0 otherwise. Panel B reports Fama-MacBeth OLS estimates for the yearly fund flow-performance relationship. Flows are measured as a growth rate relative to the fund's total net assets in the previous quarter. The independent variables include three terciles of performance in the last quarter (Low Performance, Middle Performance and High Performance) as defined in Getmansky (2005). Independent variables accounting for fund specific characteristics include a fund's monthly standard deviation of returns, size (defined as the natural logarithm of a fund's total net assets in the prior quarter), the log of a fund's age in months since inception, past quarter flow. Live is a dummy variable defined as 1 if the fund is in the Live database and 0 otherwise. HWM is a High Water Mark dummy which is equal to 1 if a high water mark provision is present and 0 otherwise. Management Fee is the fixed fee charged by the fund as a percentage of funds under management and incentive fee is the percentage fee charged by the fund if a fund's upside is above a certain threshold level. Style Effect measures the average flow at time t for a particular category. All standard errors are computed using Newey-West's (1987) method with 2 lags. * is significant at 10%, ** is significant at 5% and *** is significant at 1%.

Panel A: Effect of Asset Illiquidity and Share Restrictions on the Quarterly Fund-Flow-Performance Relationship for All CTAs

	ALL FUNDS		SYSTEMATIC		TREND		DISCRETIONARY		OPTIONS	
Variable	**Estimate**	**t-Statistic**	**Estimate**	**t-Statistic**	**Estimate**	**t-Statistic**	**Estimate**	**t-Statistic**	**Estimate**	**t-Statistic**
Intercept	0.208***	4.31	0.221***	3.93	0.242***	4.64	0.244	1.33	0.367	1.03
Low Performance	0.234***	6.76	0.168***	4.25	0.172***	4.03	0.346**	2.30	1.081**	2.04
Middle Performance	0.023	0.59	0.012	0.33	0.012	0.32	-0.005	-0.02	-0.084	-0.29
High Performance	0.131**	2.45	0.205***	3.50	0.202***	3.38	0.538	1.24	-0.011	-0.04
Low Performance*Low theta	-0.070*	-1.79	-0.058	-1.37	-0.069	-1.50	0.094	0.59	0.044	0.24
Middle Performance*Low theta	0.126**	1.98	0.126*	1.84	0.128	1.73	0.162	0.51	0.156	0.47
High Performance*Low theta	-0.002	-0.98	-0.122	-1.27	-0.103	-1.03	-0.537	-1.01	-0.125	-0.18
Standard Deviation	-0.047	-0.48	-0.164	-0.98	-0.157	-0.90	0.38	1.15	-0.731	-0.89
Log (AUM)	-0.018***	-7.26	-0.017***	-6.03	-0.018***	-6.47	-0.024**	-2.32	-0.029***	-1.72
Flow	0.156***	8.90	0.173***	5.98	0.173***	5.71	0.147	1.17	0.225***	2.13
Live	0.034***	4.49	0.041***	5.34	0.038***	4.86	-0.013	-0.47	0.005	0.08
High Water Mark	0.006	0.79	0.001	0.12	0.002	0.27	0.046*	1.90		
Management Fee	-0.040	-0.13	0.381	0.85	0.252	0.57	-0.911	-0.80	1.401	0.72
Incentive Fee	-0.003	-0.04	-0.089	-0.60	-0.104	-0.72	0.051	0.37	-0.465	-0.93
Style Effect	0.360***	8.40	0.427***	6.64	0.389***	5.14	0.532***	4.16		
No. of obs	536		378		331		134		24	
Adj.-R^2	9.82%		9.63%		9.10%		8.55%		12.96%	

Panel B: Effect of Asset Illiquidity and Share Restrictions on the Yearly Fund-Flow-Performance Relationship for All CTAs

	ALL FUNDS		SYSTEMATIC		TREND		DISCRETIONARY		OPTIONS	
Variable	**Estimate**	**t-Statistic**	**Estimate**	**t-Statistic**	**Estimate**	**t-Statistic**	**Estimate**	**t-Statistic**	**Estimate**	**t-Statistic**
Intercept	3.65***	4.12	3.329***	3.16	3.487***	3.41	5.909**	2.42	7.186	1.77
Low Performance	1.522***	3.94	2.017***	4.57	2.207***	4.50	2.069	1.25	-6.666	-1.42
Middle Performance	0.585	1.44	-0.111	-0.51	-0.122	-0.63	-0.455	-0.47	9.535	1.71
High Performance	0.820	1.25	1.442***	4.64	1.244***	4.60	3.452***	3.46	-6.690**	-2.11
Low Performance*Low theta	0.085	0.36	-0.090	-0.28	-0.175	-0.49	-0.589	-0.48	7.400	1.70
Middle Performance*Low theta	0.236	0.55	1.074	1.47	1.027	1.57	1.825	0.75	-15.26	-1.65
High Performance*Low theta	-0.230	-0.27	-1.686*	-1.98	-1.319	-1.41	-0.226	-0.06	9.395	1.60
Standard Deviation	-2.900***	-3.02	-2.538**	-2.45	-2.008	-1.74	-3.900	-1.32	-8.293**	-2.36
Log (AUM)	-0.224***	-4.40	-0.210***	-3.46	-0.216***	-3.57	-0.345**	-2.24	-0.503***	-3.39
Flow	0.073	1.59	0.102	1.23	0.117	1.20	-0.173	-1.21	0.140	0.39
Live	0.123**	2.17	0.153**	2.37	0.131**	2.56	-0.212	-1.05	0.200	0.61
High Water Mark	0.027	0.54	-0.003	-0.06	0.010	0.15	0.081	0.34		
Management Fee	-0.286	-0.12	0.495	0.13	-0.209	-0.05	6.485	0.97	23.505	0.69
Incentive Fee	-0.332	-0.46	-0.724	-0.59	-1.156	-0.94	0.673	0.35	8.789	0.6
Style Effect	1.101**	2.80	1.416**	2.85	1.584**	2.76	4.213	1.26		
No. of obs	536		378		331		134		24	
Adj.- R^2	13.02%		11.68%		11.35%		8.00%		12.22%	

Table 3.10: **Quarterly Persistence and Money Flows by Strategy**

Table 3.10 presents results for quarterly performance persistence and investor flows for the period January 1994 to December 2010. Each quarter funds are sorted into quintiles based on the preceding quarter's Fung-Hsieh alpha as well as past flows. The middle three quintiles are grouped into one portfolio resulting in three portfolios. Nine portfolios are then constructed at the intersection of both performance and flow sorts. The performance of these portfolios is then evaluated in the next quarter by equally weighting fund raw returns. Reported below are the time-series averages of the portfolio returns over the sample period January 1994 to December 2010. Reported are also average flow growth for each portfolio as well as the average number of funds in each quarter for each portfolio. Standard errors of the time series averages are reported in parentheses.

QUARTERLY PERSISTENCE AND MONEY FLOWS - BY STRATEGY

All CTAs

	Raw Return (%)	Average Growth Rate (%)	Average no. of funds
Panel A: Top Performers			
High Flows	5.64 (5.27)	66.54	13.3
Middle Flows	5.35 (5.92)	1.86	36.3
Bottom Flows	9.62 (8.29)	-24.58	9.3
High minus Low	**-3.98 (5.90)**		
Panel B: Middle Performers			
High Flows	2.36 (2.45)	63.46	31.3
Middle Flows	1.99 (3.48)	1.60	111.9
Bottom Flows	3.04 (4.14)	-26.81	36.3
High minus Low	**-0.68 (2.71)**		
Panel C: Bottom Performers			
High Flows	-0.67 (8.15)	60.97	5.95
Middle Flows	-0.63 (4.23)	0.78	36.5
Bottom Flows	0.24 (4.62)	-29.42	17.8
High minus Low	**-0.91 (6.78)**		

SYSTEMATIC

	Raw Return (%)	Average Growth Rate (%)	Average no. of funds
Panel A: Top Performers			
High Flows	4.93 (6.55)	59.68	9.3
Middle Flows	4.87 (7.12)	1.56	26.0
Bottom Flows	8.51 (8.55)	-22.47	7.2
High minus Low	**-3.58 (5.52)**		
Panel B: Middle Performers			
High Flows	2.47 (3.33)	57.41	22.1
Middle Flows	2.10 (4.48)	1.52	80.1
Bottom Flows	3.56 (5.52)	-26.41	26.2
High minus Low	**-1.09 (3.38)**		
Panel C: Bottom Performers			
High Flows	-0.37 (1.95)	62.88	4.7
Middle Flows	-0.52 (5.02)	0.60	26.3
Bottom Flows	0.46 (6.04)	-26.71	12.2
High minus Low	**-0.83 (9.78)**		

DISCRETIONARY

	Raw Return (%)	Average Growth Rate (%)	Average no. of funds
Panel A: Top Performers			
High Flows	5.76 (8.83)	82.46	3.13
Middle Flows	7.26 (6.43)	2.49	8.73
Bottom Flows	9.90 (12.54)	-26.43	2.30
High minus Low	**-4.14 (15.88)**		
Panel B: Middle Performers			
High Flows	2.05 (2.17)	79.20	7.90
Middle Flows	1.54 (1.75)	1.84	26.95
Bottom Flows	2.21 (3.55)	-27.61	8.97
High minus Low	**-0.16 (3.67)**		
Panel C: Bottom Performers			
High Flows	0.74 (5.57)	47.35	1.38
Middle Flows	-0.85 (4.21)	1.07	8.98
Bottom Flows	0.48 (6.72)	-35.84	4.66
High minus Low	**0.26 (7.39)**		

SYSTEMATIC TREND-FOLLOWERS

	Raw Return (%)	Average Growth Rate (%)	Average no. of funds
Panel A: Top Performers			
High Flows	5.04 (3.09)	60.26	8.3
Middle Flows	4.93 (7.43)	1.45	23.1
Bottom Flows	8.62 (8.81)	-21.61	6.4
High minus Low	**-3.58 (2.03)**		
Panel B: Middle Performers			
High Flows	2.44 (3.64)	54.62	19.6
Middle Flows	2.17 (4.79)	1.30	71.0
Bottom Flows	3.64 (5.60)	-25.75	23.6
High minus Low	**-1.20 (3.60)**		
Panel C: Bottom Performers			
High Flows	-1.35 (13.26)	61.66	4.5
Middle Flows	-0.50 (5.39)	0.64	23.8
Bottom Flows	0.96 (6.77)	-26.41	10.3
High minus Low	**-2.31 (9.43)**		

OPTIONS

	Raw Return (%)	Average Growth Rate (%)	Average no. of funds
Panel A: Top Performers			
High Flows	2.85 (5.73)	26.57	37.7
Middle Flows	4.18 (7.45)	8.06	1.33
Bottom Flows	2.78 (8.37)	-8.20	32.79
High minus Low	**0.07 (10.37)**		
Panel B: Middle Performers			
High Flows	1.09 (5.81)	47.33	1.07
Middle Flows	1.48 (7.45)	6.90	4.90
Bottom Flows	1.50 (4.88)	-14.79	1.39
High minus Low	**-0.41 (6.42)**		
Panel C: Bottom Performers			
High Flows	-0.54 (6.93)	8.68	1.90
Middle Flows	0.48 (8.71)	3.05	1.48
Bottom Flows	0.85 (10.79)	-16.59	1.20
High minus Low	**-1.39 (12.88)**		

Table 3.11: **Yearly Persistence and Money Flows by Strategy**

Table 3.11 presents results for yearly performance persistence and investor flows for the period January 1994 to December 2010. Each year funds are sorted into quintiles based on the preceding year's Fung-Hsieh alpha as well as past year flows. The middle three quintiles are grouped into one portfolio resulting in three portfolios. Nine portfolios are then constructed at the intersection of both performance and flow sorts. The performance of these portfolios is then evaluated in the next year by equally weighting fund raw returns. Reported below are the time-series averages of the portfolio returns over the sample period January 1994 to December 2010. Reported are also average flow growth for each portfolio as well as the average number of funds in each year for each portfolio. Standard errors of the time series averages are reported in parentheses.

YEARLY PERSISTENCE AND MONEY FLOWS - BY STRATEGY

All CTAs

	Raw Return (%)	Average Growth Rate (%)	Average no. of funds
Panel A: Top Performers			
High Flows	31.49 (10.57)	451.3	13.6
Middle Flows	22.67 (9.97)	16.7	35.4
Bottom Flows	29.10 (17.99)	-57.9	10.2
High minus Low	**2.39 (8.06)**		
Panel B: Middle Performers			
High Flows	11.5 (5.34)	379.2	31.9
Middle Flows	9.69 (6.24)	13.6	112.1
Bottom Flows	9.48 (6.27)	-57.6	35.2
High minus Low	**2.02 (4.55)**		
Panel C: Bottom Performers			
High Flows	9.31 (13.17)	300.5	5.4
Middle Flows	-0.65 (5.33)	5.01	36.6
Bottom Flows	11.85 (5.42)	-58.4	18.1
High minus Low	**-2.54 (9.31)**		

SYSTEMATIC

	Raw Return (%)	Average Growth Rate (%)	Average no. of funds
Panel A: Top Performers			
High Flows	27.65 (13.15)	387.6	8.9
Middle Flows	19.56 (11.90)	13.9	26.1
Bottom Flows	23.81 (16.87)	-54.7	7.3
High minus Low	**3.84 (2.05)**		
Panel B: Middle Performers			
High Flows	12.10 (6.01)	355.32	22.7
Middle Flows	10.22 (8.27)	11.50	79.9
Bottom Flows	9.82 (8.34)	-57.2	25.8
High minus Low	**2.28 (5.04)**		
Panel C: Bottom Performers			
High Flows	4.43 (11.30)	268.7	4.6
Middle Flows	1.07 (6.47)	7.02	26.1
Bottom Flows	3.50 (7.89)	-55.9	12.5
High minus Low	**0.93 (3.78)**		

DISCRETIONARY

	Raw Return (%)	Average Growth Rate (%)	Average no. of funds
Panel A: Top Performers			
High Flows	9.53 (21.78)	300.2	1.3
Middle Flows	6.06 (6.81)	50.8	2.1
Bottom Flows	10.95 (17.79)	-23.0	0.9
High minus Low	**-2.47 (24.34)**		
Panel B: Middle Performers			
High Flows	7.25 (20.23)	621.2	1.2
Middle Flows	5.32 (6.81)	90.9	5.3
Bottom Flows	27.05 (37.08)	-53.9	2.2
High minus Low	**-17.83 (41.03)**		
Panel C: Bottom Performers			
High Flows	2.79 (8.20)	437.7	3.2
Middle Flows	0.37 (13.15)	64.6	1.8
Bottom Flows	17.62 (37.27)	-42.3	4.5
High minus Low	**-14.83 (37.82)**		

SYSTEMATIC TREND-FOLLOWERS

	Raw Return (%)	Average Growth Rate (%)	Average no. of funds
Panel A: Top Performers			
High Flows	27.83 (13.38)	397.7	7.9
Middle Flows	19.68 (12.96)	13.4	23.4
Bottom Flows	24.64 (17.41)	-53.8	6.4
High minus Low	**3.19 (1.89)**		
Panel B: Middle Performers			
High Flows	12.35 (6.51)	350.6	19.9
Middle Flows	10.31 (8.81)	11.03	70.3
Bottom Flows	9.28 (7.73)	56.7	23.7
High minus Low	**3.07 (5.01)**		
Panel C: Bottom Performers			
High Flows	3.88 (10.79)	266.2	4.3
Middle Flows	1.72 (7.04)	6.03	24.0
Bottom Flows	4.03 (9.87	-55.5	10.3
High minus Low	**-0.15 (3.56)**		

OPTIONS

	Raw Return (%)	Average Growth Rate (%)	Average no. of funds
Panel A: Top Performers			
High Flows	2.17 (8.70)	10.6	6.3
Middle Flows	0.01 (11.70)	-1.2	1.9
Bottom Flows	2.49 (18.37)	-6.2	1.3
High minus Low	**-0.32 (20.61)**		
Panel B: Middle Performers			
High Flows	7.61 (17.60)	1633.2	0.4
Middle Flows	6.99 (16.85)	184.3	1.6
Bottom Flows	4.80 (9.77)	1.50	0.5
High minus Low	**2.81 (9.99)**		
Panel C: Bottom Performers			
High Flows	0 (0)	0	0.00
Middle Flows	4.95 (12.94)	27.4	0.6
Bottom Flows	5.62 (9.18)	-17.8	1.6
High minus Low	**-5.62 (9.18)**		

Table 3.12: **Quarterly & Yearly Persistence and Money Flows by Strategy for Top AUM Funds**

Table 3.12 presents results for quarterly and yearly performance persistence and investor flows for funds with top assets under management for the period January 1994 to December 2010. Each quarter/year funds are sorted into quintiles based on the previous year's Fung-Hsieh alpha as well as past year flows and past assets under management. The middle three quintiles are grouped into one portfolio resulting in three portfolios. Each quarter/year the funds in the top AUM quintile are used to construct nine portfolios of both performance and flow sorts. The performance of these portfolios is then evaluated in the next quarter/year by equally weighting fund raw returns. Reported below are the time-series averages of the portfolio returns over the sample period, January 1994 to December 2010.

QUARTERLY PERSISTENCE AND MONEY FLOWS - TOP AUM				
		Panel A: Top Performers		
	High Flows	**Middle Flows**	**Bottom Flows**	**High Minus Low**
All funds	5.21	4.55	9.58	-4.37
Systematic	5.42	4.27	7.98	-2.56
Trend	5.41	4.23	8.06	-2.65
Discretionary	3.51	5.88	5.70	-2.19
Options	0.58	2.68	0.33	0.25
		Panel B: Middle Performers		
	High Flows	**Middle Flows**	**Bottom Flows**	**High Minus Low**
All funds	2.06	1.93	2.96	-0.90
Systematic	2.08	2.18	3.57	-1.49
Trend	2.22	2.19	3.86	-1.64
Discretionary	1.55	1.52	2.07	-0.52
Options	1.21	1.69	1.08	0.13
		Panel C: Bottom Performers		
	High Flows	**Middle Flows**	**Bottom Flows**	**High Minus Low**
All funds	-0.53	-0.65	0.40	-0.93
Systematic	-1.16	-0.75	0.55	-1.71
Trend	-0.85	-0.68	1.04	-1.89
Discretionary	0.45	-0.68	0.99	-0.54
Options	-0.35	0.73	1.34	-1.69

YEARLY PERSISTENCE AND MONEY FLOWS - TOP AUM				
		Panel A: Top Performers		
	High Flows	**Middle Flows**	**Bottom Flows**	**High Minus Low**
All funds	28.39	19.42	23.48	4.91
Systematic	27.67	17.03	19.72	7.95
Trend	27.61	17.07	21.48	6.13
Discretionary	7.38	5.35	2.05	5.33
Options	2.17	-0.92	-1.68	3.85
		Panel B: Middle Performers		
	High Flows	**Middle Flows**	**Bottom Flows**	**High Minus Low**
All funds	11.38	9.42	10.58	0.80
Systematic	11.82	10.23	11.11	0.71
Trend	12.42	10.27	9.77	2.65
Discretionary	-0.71	5.45	22.63	-23.34
Options	1.11	3.39	0.50	0.61
		Panel C: Bottom Performers		
	High Flows	**Middle Flows**	**Bottom Flows**	**High Minus Low**
All funds	7.98	0.54	2.87	5.11
Systematic	0.13	1.15	2.90	-2.77
Trend	0.01	2.14	3.46	-3.45
Discretionary	2.00	3.85	20.16	-18.16
Options	0	5.59	2.93	-2.93

Table 3.13: **Quarterly & Yearly Persistence and Money Flows by Strategy for Bottom AUM Funds**

Table 3.13 presents results for quarterly and yearly performance persistence and investor flows for funds with the lowest (20%) assets under management for the period January 1994 to December 2010. Each quarter/year funds are sorted into quintiles based on the previous year's Fung-Hsieh alpha as well as past year flows and past assets under management. The middle three quintiles are grouped into one portfolio resulting in three portfolios. Each quarter/year the funds in the lowest AUM quintile are used to construct nine portfolios of both performance and flow sorts. The performance of these portfolios is then evaluated in the next quarter/year by equally weighting fund raw returns. Reported below are the time-series averages of the portfolio returns over the sample period January 1994 to December 2010.

QUARTERLY PERSISTENCE AND MONEY FLOWS-BOTTOM AUM				
		Panel A: Top Performers		
	High Flows	**Middle Flows**	**Bottom Flows**	**High Minus Low**
All funds	6.26	6.39	9.66	-3.40
Systematic	5.01	5.56	8.55	-3.54
Trend	4.76	5.58	8.46	-3.70
Discretionary	4.47	7.92	9.12	-4.65
Options	2.65	5.50	2.45	0.20
		Panel B: Middle Performers		
	High Flows	**Middle Flows**	**Bottom Flows**	**High Minus Low**
All funds	2.75	2.08	3.13	-0.38
Systematic	2.84	1.99	3.50	-0.66
Trend	2.62	2.15	3.43	-0.81
Discretionary	2.98	1.65	2.42	0.56
Options	0.10	1.81	1.04	-0.94
		Panel C: Bottom Performers		
	High Flows	**Middle Flows**	**Bottom Flows**	**High Minus Low**
All funds	-0.67	-0.80	0.00	-0.67
Systematic	-1.13	-0.51	0.16	-1.29
Trend	-2.49	-0.67	0.81	-3.30
Discretionary	0.61	-1.02	0.00	0.61
Options	-0.19	-0.24	-0.41	0.22

YEARLY PERSISTENCE AND MONEY FLOWS -BOTTOM AUM				
		Panel A: Top Performers		
	High Flows	**Middle Flows**	**Bottom Flows**	**High Minus Low**
All funds	34.78	27.05	31.56	3.22
Systematic	28.17	22.34	23.08	5.09
Trend	26.97	22.24	24.01	2.96
Discretionary	2.15	4.20	8.91	-6.76
Options	0.00	1.02	4.17	-4.17
		Panel B: Middle Performers		
	High Flows	**Middle Flows**	**Bottom Flows**	**High Minus Low**
All funds	11.52	10.17	8.77	2.75
Systematic	12.54	10.19	8.54	4.00
Trend	11.43	10.28	8.34	3.09
Discretionary	9.40	4.77	16.63	-7.23
Options	6.49	6.22	4.30	2.19
		Panel C: Bottom Performers		
	High Flows	**Middle Flows**	**Bottom Flows**	**High Minus Low**
All funds	11.09	-2.32	1.44	9.65
Systematic	7.05	1.11	4.02	3.03
Trend	7.40	1.25	4.56	2.84
Discretionary	1.39	-3.53	7.76	-6.37
Options	0.00	-0.61	4.51	-4.51

Table 3.14: **The Performance of CTA Investors' Flows by Strategy**

Table 3.14 presents the performance of CTA flows for each CTA strategy for the period January 1994 to December 2010. The first column shows Grinblatt and Titman's (1993) measure with respective t-values reported in column three. The remaining columns show time-series average and quarterly raw return of a zero-cost portfolio both flow-weighted and equally weighted. These portfolios are generated for each quarter by going long on the funds that had experienced positive flows in the previous quarter and shorting those funds that lost assets in the previous quarter. Both equally-weighted as well as cash-flow weighted portfolios are calculated with time series t-values shown in the adjacent columns. Portfolio values are reported in yearly percentages. * is significant at 10%, ** is significant at 5% and *** is significant at 1%.

	GT (%)	**Time-Series t-value**	**Flow_Weighted Zero-Cost Portfolio (%)**	**Time-Series t-value**	**Equally_Weighted Zero-Cost Portfolio (%)**	**Time-Series t-value**
ALL CTAS	-0.01	-0.42	-0.23	-0.76	-0.27	-1.66
SYSTEMATIC	-0.02	-0.68	-0.26	-0.87	-0.27	-1.38
TREND	-0.02	-0.51	-0.16	-0.49	-0.23	-1.10
Short-Term	-0.08	-1.48	0.16	0.24	-0.33	-0.75
Medium-Term	-0.01	-0.47	-0.13	-0.37	0.02	0.09
Long-Term	0.07	1.24	1.01	1.43	-0.55	-1.12
Patter Rec	-0.08	-0.70	-0.29	-0.29	-0.04	-0.06
Spread/RV	-0.13*	-1.95	-0.45	-0.77	-0.89**	-2.16
DISCRETIONARY	0.04	0.76	0.08	0.14	-0.14	-0.51
Fundamental	0.04	0.88	-0.17	-0.20	0.06	0.14
Technical	0.03	0.38	-0.48	-0.75	-0.24	-0.56
Fundamental &Technical	-0.19	-1.52	-0.35	-0.33	-0.41	-0.60
Spread/RV	0.14	1.09	-0.60	-0.39	-1.26	-0.82
OPTIONS	-0.06	-0.31	1.81	1.56	0.83	0.81

Table 3.15: **Portfolios Sorted on Flows**

Table 3.15 reports portfolio sorts by quarterly flow for the period January 1994 to December 2010. Funds are sorted into three equal-size portfolios based on their flow in the prior quarter. Portfolios are then equally-weighted and re-balanced monthly. Panel A reports the average portfolio returns in excess of the three-month Treasury Bills. Columns two to four report the average portfolio returns for low, middle and high flows, whilst the last column reports the average return of the difference portfolio between tercile 3 and tercile 1. Panel B presents the same results but for risk-adjusted returns using BIC regression and Fung-Hsieh factors augmented with the GSCI index. t-statistics are reported below each return in italics.

Panel A: Excess Returns

	Lowest Flow	**Middle Flow**	**Highest Flow**	**High-Low Flow**
ALL CTAs	1.90	2.04	1.57	-0.34
	4.05	*4.21*	*4.05*	*-1.65*
SYSTEMATIC	1.83	1.91	1.61	-0.21
	3.06	*3.10*	*3.12*	*-0.85*
TREND	1.81	2.00	1.72	-0.09
	2.86	*3.00*	*3.12*	*-0.36*
Short-Term	1.97	1.50	1.16	-0.81
	4.25	*4.67*	*2.71*	*-1.51*
Medium-Term	1.66	1.93	1.88	0.22
	2.48	*2.80*	*3.13*	*0.78*
Long-Term	2.45	2.22	2.60	0.15
	2.52	*2.22*	*2.59*	*0.26*
Pattern Rec	2.76	1.35	2.50	-0.33
	2.64	*1.66*	*2.76*	*-0.35*
Spread/RV	1.43	1.48	0.31	-1.12**
	2.66	*3.44*	*0.89*	*-2.12*
DISCRETIONARY	1.82	2.41	1.50	-0.32
	6.21	*5.76*	*5.49*	*-1.04*
Fundamental	1.33	2.56	1.39	0.06
	2.53	*3.87*	*3.19*	*0.11*
Technical	2.05	2.57	1.41	-0.64
	4.89	*5.16*	*3.12*	*-1.27*
Fundamental &Technical	2.32	2.67	1.50	-0.82
	3.78	*3.62*	*3.40*	*-1.12*
Spread/RV	2.30	1.60	0.61	-1.56
	2.34	*2.56*	*1.01*	*-1.30*
OPTIONS	1.29	2.19	2.57	1.06
	1.31	*2.67*	*3.07*	*0.85*

Panel B: Fung-Hsieh Alphas				
	Lowest Flow	**Middle Flow**	**Highest Flow**	**High-Low Flow**
ALL CTAs	0.02	0.02	0.01	-0.01
	5.85	*5.64*	*4.89*	*-1.72*
SYSTEMATIC	0.02	0.02	0.02	0.00
	4.50	*4.75*	*5.73*	*-0.61*
TREND	0.02	0.03	0.02	0.00
	4.17	*4.63*	*5.74*	*-1.10*
Short-Term	0.02	0.02	0.02	-0.01
	6.13	*6.22*	*4.62*	*-1.60*
Medium-Term	0.01	0.03	0.03	0.00
	3.38	*4.65*	*5.71*	*1.25*
Long-Term	0.02	0.02	0.02	0.00
	3.27	*2.61*	*2.83*	*-0.75*
Pattern Rec	0.04	0.02	0.03	-0.01
	4.12	*2.92*	*3.32*	*-0.50*
Spread/RV	0.01	0.01	0.00	-0.01**
	2.13	*2.48*	*0.40*	*-2.64*
DISCRETIONARY	0.02	0.03	0.02	0.00
	5.78	*6.75*	*6.04*	*-0.76*
Fundamental	0.01	0.03	0.01	0.00
	1.95	*4.22*	*3.24*	*0.44*
Technical	0.02	0.02	0.02	0.00
	4.44	*5.62*	*2.75*	*-0.78*
Fundamental &Technical	0.02	0.02	0.02	-0.01
	3.19	*3.86*	*4.01*	*-0.91*
Spread/RV	0.03	0.02	0.01	-0.01
	2.67	*3.05*	*2.02*	*-1.24*
OPTIONS	0.00	0.03	0.03	0.01
	-0.37	*3.86*	*3.63*	*0.48*

Table 3.16: **Holding Period Returns of Portfolios sorted on Flows**

Table 3.16 presents the differences in raw returns between cash-flow weighted and equally-weighted portfolios of all CTAs formed based on previous quarter cash flows for the period January 1994 to December 2010. Specifically, each quarter CTA funds are sorted into the investment or divestment portfolio if the previous quarter flows were positive or negative respectively. Compounded returns are then reported from one to eight quarters after the ranking as well as the average return in the ranking period. This procedure is repeated each quarter with portfolios rebalanced quarterly. The table reports the time series averages of cross-sectional averages of returns. Panel A reports returns for the investment portfolio, Panel B for the divestment portfolio and Panel C shows the difference between the investment and divestment portfolios. The table also reports differences between cash-flow weighted and equally weighted portfolio returns and their standard errors.

The Performance of Investors' CTA Portfolios - All CTAs

Panel A: Investment Portfolio - Weighted Average of Quarterly Returns									
	Ranking Period	Evaluation Period (Quarters)							
	0	1	2	3	4	5	6	7	8
CashFlow Weighted	0.0392	0.0253	0.0251	0.0261	0.0264	0.0260	0.0260	0.0255	0.0252
Equally Weighted	0.0263	0.0259	0.0262	0.0264	0.0271	0.0279	0.0287	0.0295	0.0303
Difference	0.0129	-0.0006	-0.0011	-0.0003	-0.0007	-0.0020	-0.0027	-0.0040	-0.0050
S.E.	0.0195	0.0171	0.0117	0.0110	0.0105	0.0083	0.0081	0.0086	0.0087
Panel B: Divestment Portfolio - Weighted Average of Quarterly Returns									
	Ranking Period	Evaluation Period (Quarters)							
	0	1	2	3	4	5	6	7	8
CashFlow Weighted	0.0365	0.0276	0.0253	0.0253	0.0258	0.0253	0.0254	0.0252	0.0252
Equally Weighted	0.0314	0.0286	0.0288	0.0292	0.0304	0.0311	0.0318	0.0329	0.0338
Difference	0.0051	-0.0009	-0.0035	-0.0039	-0.0046	-0.0058	-0.0064	-0.0077	-0.0086
S.E.	0.0150	0.0121	0.0083	0.0068	0.0075	0.0068	0.0067	0.0065	0.0068
Panel C: Investment-Divestment Portfolios - Weighted Average of Quarterly Returns									
	Ranking Period	Evaluation Period (Quarters)							
	0	1	2	3	4	5	6	7	8
CashFlow Weighted	0.0027	-0.0023	-0.0003	0.0008	0.0006	0.0007	0.0006	0.0003	0.0000
S.E.	0.0278	0.0258	0.0156	0.0134	0.0138	0.0111	0.0112	0.0112	0.0117
Equally-Weighted	-0.0051	-0.0027	-0.0026	-0.0028	-0.0033	-0.0031	-0.0031	-0.0034	-0.0036
S.E.	0.0118	0.0135	0.0095	0.0073	0.0075	0.0064	0.0067	0.0070	0.0071

Table 3.17: **Holding Period Returns of Portfolios sorted on Flows by Strategy**

Table 3.17 presents the differences in raw returns between cash-flow weighted and equally-weighted portfolios of all CTAs formed based on previous quarter cash flows for the period January 1994 to December 2010. Specifically, each quarter CTA funds are sorted into the investment or divestment portfolio if the previous quarter flows were positive or negative respectively. Compounded returns are then reported from one to eight quarters after the ranking as well as the average return in the ranking period. This procedure is repeated each quarter with portfolios rebalanced quarterly. The table reports the time series averages of cross-sectional averages of returns. Panel A reports returns for the investment portfolio, Panel B for the divestment portfolio and Panel C shows the difference between the investment and divestment portfolios. The table also reports differences between cash-flow weighted and equally weighted portfolio returns and their standard errors.

Investment-Divestment Portfolios - Weighted Average of Quarterly Returns By Strategy									
SYSTEMATIC	Ranking Period	Evaluation Period (Quarters)							
	0	1	2	3	4	5	6	7	8
CashFlow Weighted	0.0014	-0.0026	-0.0011	0.0004	0.0006	0.0015	0.0016	0.0014	0.0017
S.E.	0.0263	0.0256	0.0164	0.0123	0.0115	0.0104	0.0095	0.0097	0.0099
Equally-Weighted	-0.0068	-0.0027	-0.0028	-0.0022	-0.0029	-0.0025	-0.0023	-0.0025	-0.0021
S.E.	0.0150	0.0162	0.0104	0.0074	0.0071	0.0064	0.0061	0.0062	0.0064
TREND	Ranking Period	Evaluation Period (Quarters)							
	0	1	2	3	4	5	6	7	8
CashFlow Weighted	0.0007	-0.0016	-0.0010	0.0003	0.0007	0.0016	0.0017	0.0016	0.0017
S.E.	0.0300	0.0280	0.0176	0.0129	0.0126	0.0112	0.0101	0.0104	0.0109
Equally-Weighted	-0.0074	-0.0023	-0.0024	-0.0016	-0.0023	-0.0020	-0.0018	-0.0020	-0.0018
S.E.	0.0175	0.0173	0.0112	0.0078	0.0076	0.0067	0.0065	0.0064	0.0068
SYSTEMATIC S-T	Ranking Period	Evaluation Period (Quarters)							
	0	1	2	3	4	5	6	7	8
CashFlow Weighted	-0.0060	0.0016	0.0013	0.0040	0.0046	0.0034	0.0026	0.0024	0.0034
S.E.	0.0560	0.0548	0.0366	0.0309	0.0259	0.0249	0.0235	0.0213	0.0203
Equally-Weighted	-0.0107	-0.0033	-0.0038	-0.0021	-0.0013	-0.0023	-0.0024	-0.0022	-0.0014
S.E.	0.0346	0.0366	0.0277	0.0228	0.0200	0.0184	0.0176	0.0174	0.0174
SYSTEMATIC M-T	Ranking Period	Evaluation Period (Quarters)							
	0	1	2	3	4	5	6	7	8
CashFlow Weighted	0.0012	-0.0013	-0.0011	-0.0003	0.0003	0.0013	0.0017	0.0015	0.0007
S.E.	0.0345	0.0302	0.0189	0.0152	0.0149	0.0132	0.0117	0.0124	0.0122
Equally-Weighted	-0.0056	0.0002	-0.0017	-0.0011	-0.0022	-0.0016	-0.0012	-0.0018	-0.0022
S.E.	0.0202	0.0199	0.0136	0.0105	0.0099	0.0080	0.0072	0.0076	0.0078
SYSTEMATIC L-T	Ranking Period	Evaluation Period (Quarters)							
	0	1	2	3	4	5	6	7	8
CashFlow Weighted	-0.0118	0.0101	0.0100	0.0082	0.0079	0.0086	0.0065	0.0086	0.0086
S.E.	0.0682	0.0588	0.0462	0.0347	0.0298	0.0265	0.0245	0.0277	0.0275
Equally-Weighted	-0.0107	-0.0055	-0.0018	-0.0011	-0.0012	-0.0014	-0.0030	-0.0004	0.0008
S.E.	0.0387	0.0411	0.0257	0.0244	0.0202	0.0170	0.0165	0.0167	0.0158

Table 3.17 Continued

SYSTEMATIC SPREA/RV	Ranking Period	Evaluation Period (Quarters)							
	0	1	2	3	4	5	6	7	8
CashFlow Weighted	0.0070	-0.0045	0.0022	-0.0011	-0.0013	0.0003	0.0001	-0.0016	0.0006
S.E.	0.0555	0.0494	0.0329	0.0305	0.0251	0.0216	0.0202	0.0257	0.0200
Equally-Weighted	-0.0017	-0.0089	-0.0035	-0.0085	-0.0082	-0.0060	-0.0065	-0.0060	-0.0045
S.E.	0.0292	0.0346	0.0249	0.0241	0.0195	0.0204	0.0181	0.0162	0.0170
DISCRETIONARY	Ranking Period	Evaluation Period (Quarters)							
	0	1	2	3	4	5	6	7	8
CashFlow Weighted	0.0064	0.0008	0.0004	0.0018	0.0008	-0.0015	-0.0018	-0.0019	-0.0026
S.E.	0.0606	0.0504	0.0349	0.0354	0.0349	0.0309	0.0330	0.0318	0.0311
Equally-Weighted	-0.0004	-0.0014	-0.0010	-0.0033	-0.0036	-0.0045	-0.0038	-0.0037	-0.0049
S.E.	0.0243	0.0230	0.0187	0.0183	0.0175	0.0171	0.0172	0.0168	0.0179
FUNDAMENTAL	Ranking Period	Evaluation Period (Quarters)							
	0	1	2	3	4	5	6	7	8
CashFlow Weighted	0.0087	-0.0017	-0.0019	0.0003	-0.0063	-0.0036	-0.0055	-0.0055	-0.0073
S.E.	0.0920	0.0709	0.0396	0.0372	0.0691	0.0586	0.0637	0.0617	0.0629
Equally-Weighted	0.0063	0.0006	-0.0008	0.0009	0.0005	0.0004	0.0016	0.0013	-0.0006
S.E.	0.0415	0.0369	0.0336	0.0323	0.0307	0.0316	0.0319	0.0333	0.0358
TECHNICAL	Ranking Period	Evaluation Period (Quarters)							
	0	1	2	3	4	5	6	7	8
CashFlow Weighted	0.0102	-0.0048	-0.0046	-0.0037	-0.0019	-0.0043	-0.0054	-0.0060	-0.0051
S.E.	0.0875	0.0533	0.0379	0.0345	0.0337	0.0294	0.0302	0.0293	0.0314
Equally-Weighted	0.0024	-0.0024	-0.0052	-0.0071	-0.0066	-0.0079	-0.0065	-0.0068	-0.0094
S.E.	0.0423	0.0358	0.0283	0.0251	0.0283	0.0291	0.0279	0.0282	0.0272
FUNDAMENTAL & TECHNICAL	Ranking Period	Evaluation Period (Quarters)							
	0	1	2	3	4	5	6	7	8
CashFlow Weighted	-0.0274	-0.0035	-0.0018	-0.0028	-0.0059	-0.0079	-0.0056	-0.0054	-0.0060
S.E.	0.1642	0.0881	0.0681	0.0739	0.0705	0.0662	0.0638	0.0654	0.0710
Equally-Weighted	-0.0104	-0.0041	-0.0006	-0.0052	-0.0055	-0.0073	-0.0074	-0.0065	-0.0068
S.E.	0.0571	0.0569	0.0428	0.0408	0.0380	0.0372	0.0348	0.0344	0.0366
OPTONS	Ranking Period	Evaluation Period (Quarters)							
	0	1	2	3	4	5	6	7	8
CashFlow Weighted	0.0119	0.0177	0.0141	0.0068	0.0027	0.0004	-0.0023	-0.0050	-0.0085
S.E.	0.0864	0.0939	0.0626	0.0631	0.0567	0.0522	0.0495	0.0455	0.0471
Equally-Weighted	0.0075	0.0083	0.0039	0.0007	0.0035	0.0028	-0.0053	-0.0101	-0.0088
S.E.	0.0696	0.0838	0.0533	0.0408	0.0552	0.0485	0.0502	0.0485	0.0472

Table 3.18: **CTA Four-Factor Model Conditional on CTA Flows by Strategy**

Table 3.18 presents regression coefficients from regressing monthly returns of asset-weighted strategy indices on the standardized sum of the past year's strategy flows, lagged aggregate strategy log(AUM), the square of lagged aggregate strategy log(AUM) and lagged monthly number of funds in the strategy. Strategies are shown in rows and respective coefficients in columns. The last column reports R^2. I use Newey-West heteroskedasticity and autocorrelation consistent standard errors with 11 lags. * is significant at 10%, ** is significant at 5% and *** is significant at 1%.

	Constant	ϕ	AUM	AUM^2	No. of funds	R^2
All funds	-1.412	-0.017*	0.116	-0.002	0.000	0.012
Systematic	-1.293	-0.017	0.107	-0.002	0.000	0.012
Trend-followers	-0.895	-0.022	0.078	-0.002	0.000	0.013
Short-Term Trend-Followers	0.716	-0.004	-0.058	0.001	0.000	0.149
Medium-Term Trend-Followers	-0.118	-0.011	0.014	0.000	0.000	0.005
Long-Term Trend-Followers	2.086	-0.017	-0.176	0.004	0.000	0.010
Systematic Spread/RV	1.028***	0.000	-0.093***	0.002***	-0.001***	0.044
Pattern Recognition	-0.470	-0.006	0.051	-0.001	0.001	0.017
Discretionary	-0.089	-0.011***	0.009	0.000	0.000	0.014
Fundamental	-0.825	-0.002	0.074	-0.002	0.000	0.016
Technical	-2.015	-0.015***	0.200	-0.005	0.001***	0.030
Fundamental & Technical	-1.349	-0.003	0.126	-0.003	0.000	0.003
Discretionary Spread/RV	-0.473*	0.005	0.0490*	-0.001*	0.000	0.036
Options	0.099	0.002	-0.007	0.000	0.000	0.024

Table 3.19: **CTA Six-Factor Model Conditional on CTA Flows by Strategy**

Table 3.19 presents regression coefficients from regressing monthly returns of asset-weighted strategy indices on the standardised sum of the past year's strategy flows, S&P 500, the Fama-French size factor SMB, HML value factor, Goldman Sachs Commodities Index and Carhart Momentum factor (UMD). Strategies are shown in rows and respective coefficients in columns. The last column reports R^2. I use Newey-West heteroskedasticity and autocorrelation consistent standard errors with 11 lags. * is significant at 10%, ** is significant at 5% and *** is significant at 1%.

	Constant	ϕ	S&P 500	SMB	HML	GSCI	UMD	R^2
All funds	0.012***	-0.010	-0.058	0.000	0.000	0.065*	0.001*	0.059
Systematic	0.012***	-0.010	-0.068	0.000	0.000	0.068*	0.001	0.052
Trend-followers	0.013***	-0.013	-0.079	0.000	0.000	0.070	0.001	0.053
Short-Term Trend-followers	0.002***	0.007	-0.058	-0.001***	0.000	0.062***	0.000*	0.078
Medium-Term Trend-followers	0.011***	-0.003	-0.113	0.000	0.001	0.053	0.001	0.049
Long-Term Trend-followers	0.010***	-0.015	-0.030	0.001	0.001	0.207***	0.001**	0.117
Systematic Spread/RV	0.007***	0.001	0.069	0.000	0.000	0.012	0.000	0.031
Pattern Recognition	0.010***	-0.005	-0.113***	0.000	0.000	0.039	0.001***	0.079
Discretionary	0.010***	-0.010***	0.032	0.000	0.000	0.065***	0.000	0.133
Fundamental	0.007***	-0.003	-0.047	0.000	0.000	0.038	0.000	0.037
Technical	0.009***	-0.006**	-0.008	0.001	0.000	0.048*	0.000	0.066
Fundamental & Technical	0.008***	-0.004	0.118***	0.000	0.000	0.093***	0.000	0.114
Discretionary Spread/RV	0.004*	0.005	-0.083**	0.000	0.000	-0.057**	0.000	0.095
Options	0.002	0.008**	0.110***	0.001*	0.000	0.048*	0.001***	0.133

Figure 3.1: **Number of CTA Funds vs. CTA AUM**

Figure 1 shows the evolution of the number of CTAs (blue dashed line) as well as the total Assets-Under-Management (AUM) in billions US$ (green solid line) for the entire CTA industry.

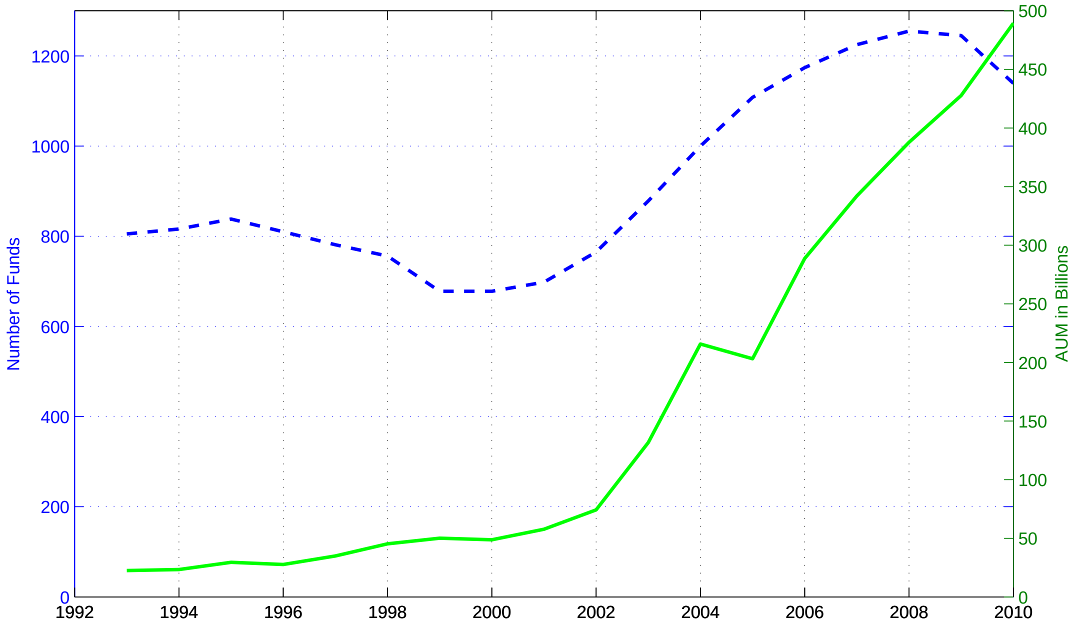


Figure 3.2: **Cumulative Quarterly Flows for Systematic and Discretionary CTAs**

The X axis shows the dates for which cumulative flow index is plotted on a logarithmic Y scale. The index begins in December 1993 at value 100 and successive values are each given by multiplying by the next period compounded growth in equally-weighted quarterly flows. Data are for December 1993 to December 2010 period.

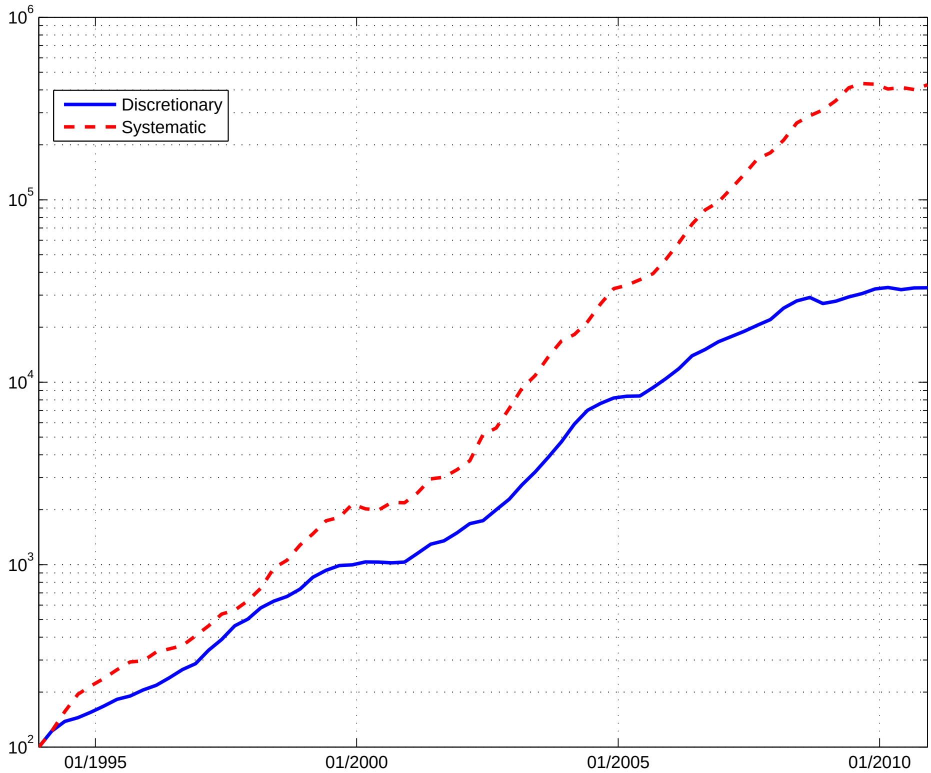
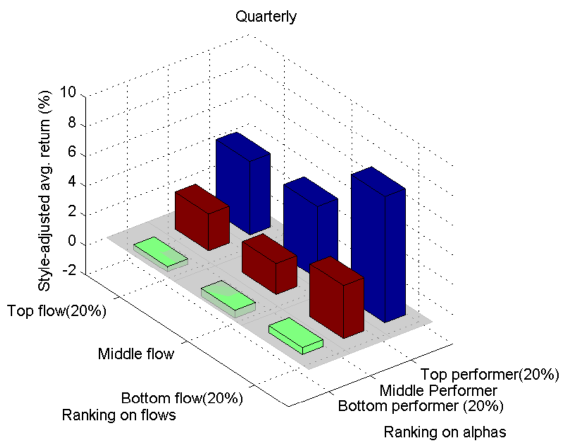


Figure 3.3: **Persistence and Money Flows for Systematic CTAs**

Each quarter/year CTAs are sorted into quintiles based on past Fung-Hsieh alpha and fund flows. Portfolios are constructed at the intersection of both sorts and nine portfolios are formed. The middle three quintiles are grouped into one portfolio. Portfolio returns are computed each quarter subsequent to ranking. Each bar represent a time-series average of portfolio returns. Data are for January 1994 to December 2010 period.

Panel A: Quarterly Persistence and Flows



Panel B: Yearly Persistence and Flows

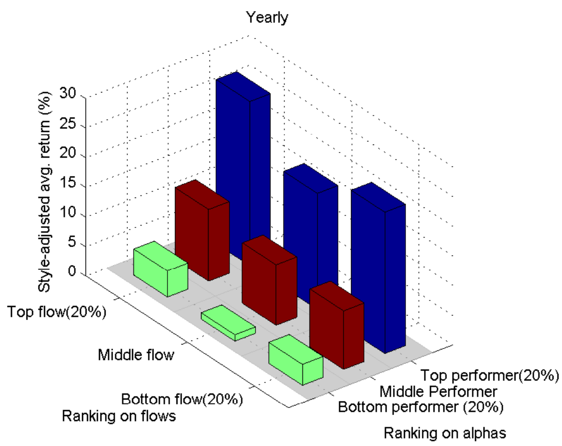
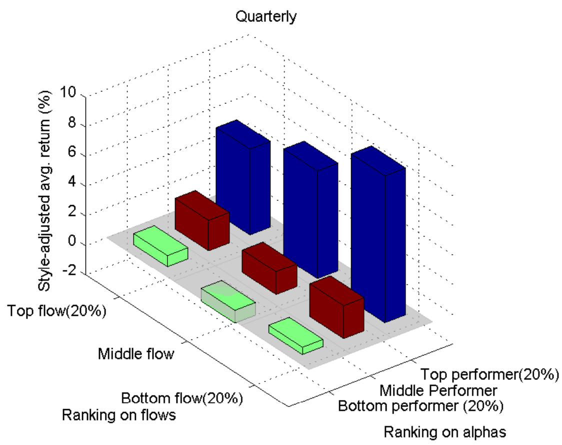


Figure 3.4: **Persistence and Money Flows for Discretionary CTAs**

Each quarter/year CTAs are sorted into quintiles based on past Fung-Hsieh alpha and fund flows. Portfolios are constructed at the intersection of both sorts and nine portfolios are formed. the middle three quintiles are grouped into one portfolio. Portfolio returns are computed each quarter subsequent to ranking. Each bar represents a time-series average of portfolio returns. Data are for January 1994 to December 2010 period.

Panel A: Quarterly Persistence and Flows



Panel B: Yearly Persistence and Flows

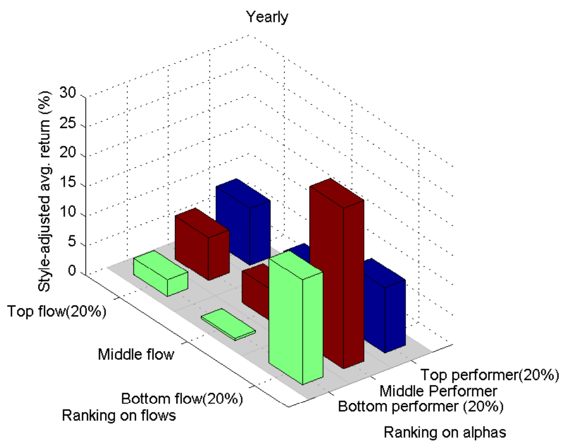
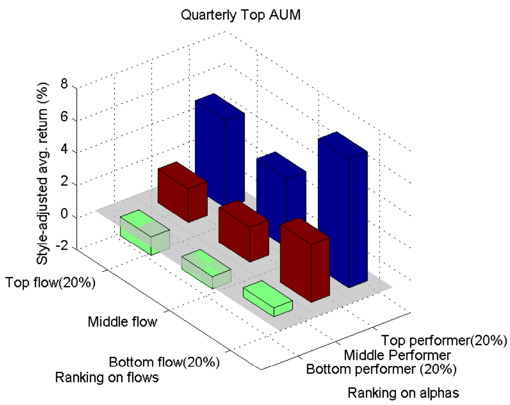


Figure 3.5: **Quarterly Persistence and Money Flows for Top AUM Systematic and Discretionary CTAs**

Each quarter CTAs are sorted into quintiles based on past Fung-Hsieh alpha and fund flows and assets under management. For the top quintile of assets under management portfolios are constructed at the intersection of performance and flow sorts and nine portfolios are formed. The middle three quintiles are grouped into one portfolio. Portfolio returns are computed each quarter subsequent to ranking. Each bar represent a time-series average of portfolio returns. Data are for January 1994 to December 2010 period.

Panel A: Systematic CTAs

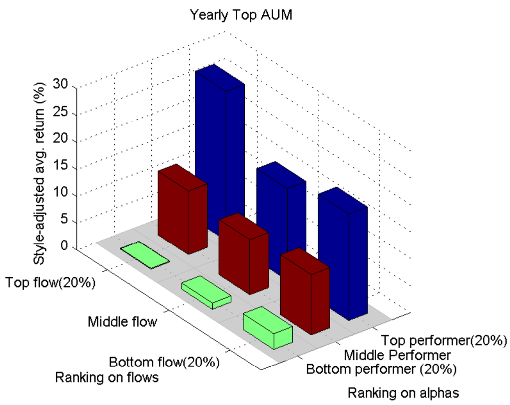


Panel B: Discretionary CTAs

Figure 3.6: **Yearly Persistence and Money Flows for Top AUM Systematic and Discretionary CTAs**

Each year CTAs are sorted into quintiles based on past Fung-Hsieh alpha and fund flows and assets under management. For the top quintile of assets under management portfolios are constructed at the intersection of performance and flow sorts and nine portfolios are formed. The middle three quintiles are grouped into one portfolio. Portfolio returns are computed each quarter subsequent to ranking. Each bar represent a time-series average of portfolio returns. Data are for January 1994 to December 2010 period.

Panel A: Systematic CTAs



Panel B: Discretionary CTAs

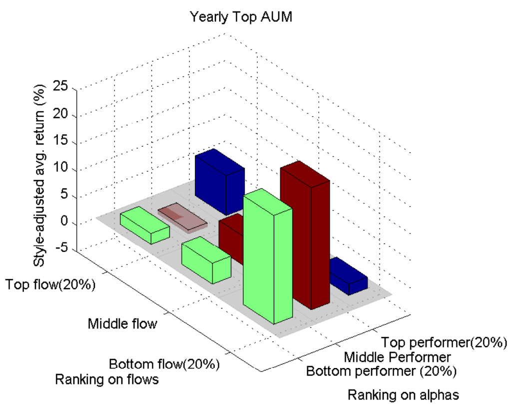
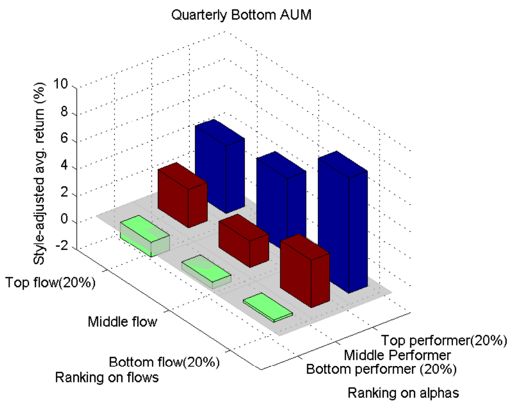


Figure 3.7: **Quarterly Persistence and Money Flows for Bottom AUM Systematic and Discretionary CTAs**

Each quarter CTAs are sorted into quintiles based on past Fung-Hsieh alpha and fund flows and assets under management. For the bottom quintile of assets under management portfolios are constructed at the intersection of performance and flow sorts and nine portfolios are formed. The middle three quintiles are grouped into one portfolio. Portfolio returns are computed each quarter subsequent to ranking. Each bar represent a time-series average of portfolio returns. Data are for January 1994 to December 2010 period.

Panel A: Systematic CTAs



Panel B: Discretionary CTAs

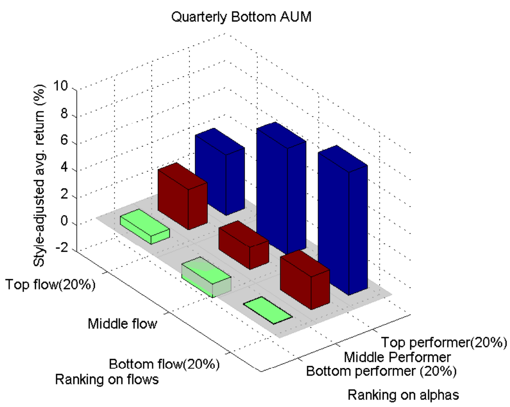
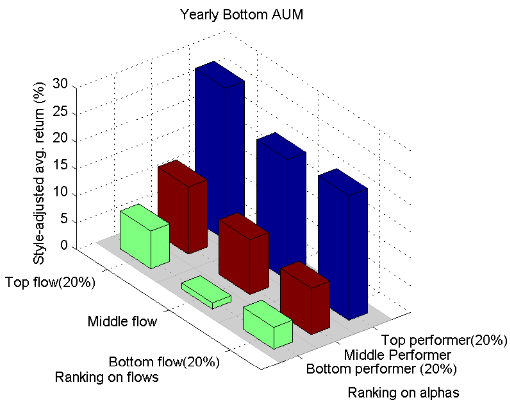


Figure 3.8: **Yearly Persistence and Money Flows for Bottom AUM Systematic and Discretionary CTAs**

Each year CTAs are sorted into quintiles based on past Fung-Hsieh alpha and fund flows and assets under management. For the bottom quintile of assets under management portfolios are constructed at the intersection of performance and flow sorts and nine portfolios are formed. The middle three quintiles are grouped into one portfolio. Portfolio returns are computed each quarter subsequent to ranking. Each bar represent a time-series average of portfolio returns. Data are for January 1994 to December 2010 period.

Panel A: Systematic CTAs



Panel B: Discretionary CTAs

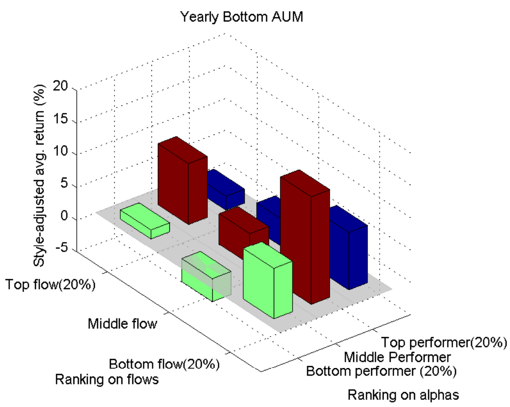
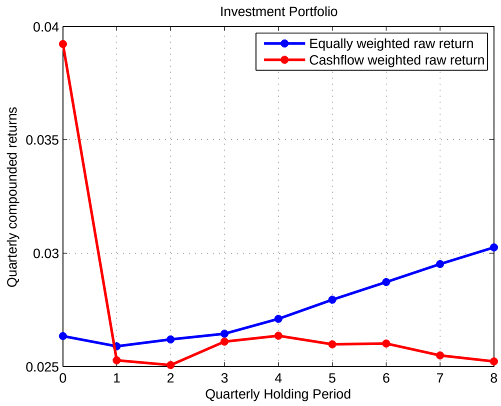


Figure 3.9: **Time-Series Averages for Flow-Weighted and Equally-Weighted Investment Portfolios of CTA returns for Different Holding Periods for All CTAs**

Panel A shows time-series averages for the portfolio of CTAs that invests each quarter into funds that have received inflows in the prior quarter. The Y axis shows quarterly compounded returns evaluated over different holding periods up to eight quarters shown on the X axis. The figure shows both equally-weighted as well as cash-flow weighted portfolio returns. Panel B shows returns for the divestment portfolio which is the portfolio formed of funds with negative cash flows. Data are for January 1994 to December 2010 period.

Panel A: Investment Portfolio



Panel B: Divestment Portfolio

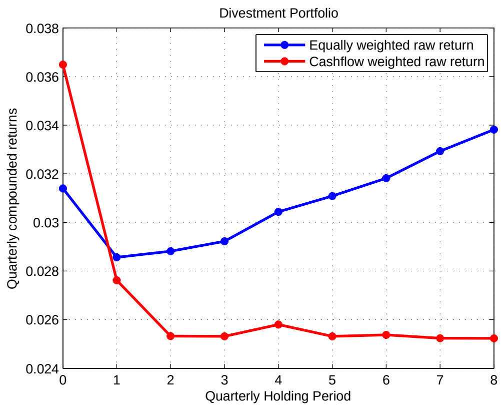
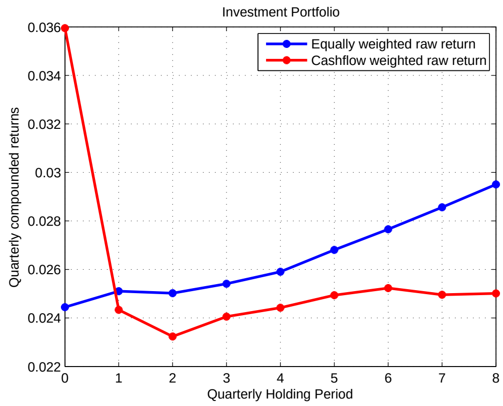


Figure 3.10: **Time-Series Averages for Flow-Weighted and Equally-Weighted Investment Portfolios for Systematic CTAs for Different Holding Periods**

Panel A shows time-series averages of the portfolio of CTAs that invests each quarter into funds that have received inflows in the prior quarter. The Y axis shows quarterly compounded returns evaluated over different holding periods up to eight quarters shown on the X axis. The figure shows both equally-weighted as well as cash-flow weighted portfolio returns. Panel B shows returns for the divestment portfolio which is the portfolio formed of funds with negative cash flows. Data are for January 1994 to December 2010 period.

Panel A: Investment Portfolio



Panel B: Divestment Portfolio

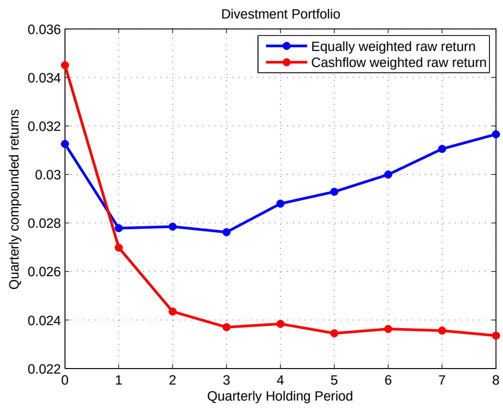
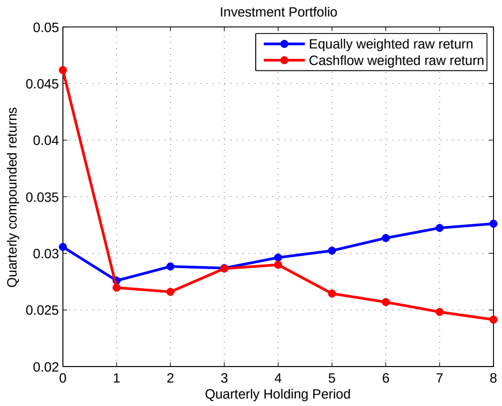


Figure 3.11: **Time-Series Averages for Flow-Weighted and Equally-Weighted Investment Portfolios for Discretionary CTAs for Different Holding Periods**

Panel A shows time-series averages of the portfolio of CTAs that invests each quarter into funds that have received inflows in the prior quarter. The Y axis shows quarterly compounded returns evaluated over different holding periods up to eight quarters shown on the X axis. The figure shows both equally-weighted as well as cash-flow weighted portfolio returns. Panel B shows returns for the divestment portfolio which is the portfolio formed of funds with negative cash flows. Data are for January 1994 to December 2010 period.

Panel A: Investment Portfolio



Panel B: Divestment Portfolio

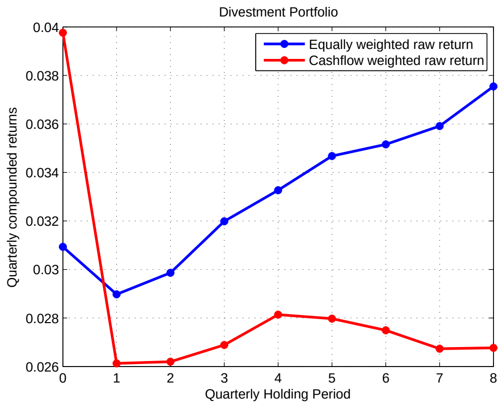
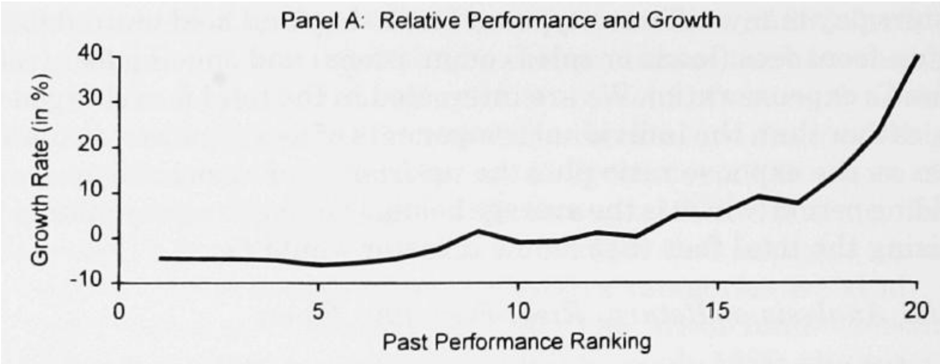


Figure 3.12: **Relative Performance and Asset Growth in the Mutual Fund Industry - Convex Relationship - reproduced from Sirri and Tufano (1998)**



Conclusion

In this thesis I use a novel CTA strategy classification to highlight the effects of previously documented ‘stylized facts’ on CTA survival, performance, performance persistence and the fund-flow performance relationship. I use the longest period studied in the CTA literature and show that the ‘stylized facts’ are sensitive to the particular CTA strategy. I provide the first comprehensive empirical evidence that there are indeed many differences between systematic and discretionary CTAs.

In the first part of the thesis, I implement a survival analysis to examine the factors determining CTA failure. By collecting missing information on the reasons for exit from the database, I show that the attrition rate is not the same as the failure rate of CTAs. In particular, I separate funds in the CTA graveyard database into those that are still operating but stopped reporting, those that have liquidated for other reasons such as fund merging and those that have truly failed. I show that the filters proposed in the hedge fund literature to identify real failures are not always adequate and thus further extend them. I re-examine the attrition rate in the CTA literature and show that the real failure rate is not as high as previously documented, even when taking the recent 2008 crisis into account. I further find that the failure rate of systematic CTAs is lower than that of discretionary CTAs.

Following earlier literature on CTA survival, I progress the methodology by separating exit types in the survival analysis as well as incorporating time-varying covariates into the Cox (1972) proportional hazards model. I thus clarify the roles of performance, size, past asset inflows, age, HWM and various risk measures in predicting CTA failure. I find that downside risk measures such as tail risk are superior to standard deviation in predicting CTA failure. I also find that past performance is always significant after controlling for other variables such as risk, past flow, size, management and incentive fees with a HWM provision. I find that age has no effect on predicting CTA survival. Moreover, these effects are strongest when exit is defined as real failure rather than exit from the database. This underscores the need to separate the graveyard into different exit types to avoid blurring the effect of predictor variables.

These results provide interesting implications for investors, database providers and future academic studies. I show that it is important to determine the reasons CTA funds exit from the database. Since I find limited evidence of capacity constraints among CTAs and I show that few funds choose to stop reporting to the database whilst continuing to operate, this leaves then it is important to really identify reasons for exit. Database providers should put more effort into collecting this information in the future. Although CTAs are not legally required to provide any information, one way to circumvent this problem is by an agreement whereby a fund can report to a database only on a condition that it provides reason for exit once it chooses to no longer report. Secondly, investors should be aware that not all funds in the graveyard are real failures. By separating the graveyard into various exit types, it will allow investors to better estimate the expected lifetimes of CTAs thereby improving investor outcomes. Thirdly, the proposed filters will help future research on CTA survival.

In the second part of this thesis I study the performance, risk and performance persistence of CTA strategies over the 1994 to 2010 period, the longest period studied in the CTA literature. I find that the returns of systematic CTAs are largely driven by their exposure to the seven risk factors of Fung and Hsieh (2004a) model extended with additional trend-following factors on interest rates and stocks and including excess return on the GSCI index. I find that this model leaves a large amount of unexplained variance for discretionary funds indicating that it is systematic funds that indeed follow futures-based trend-following strategies, a result that resonates with the conclusions of Kazemi and Li (2009). I further find that systematic CTAs have different structural breaks than those identified previously in the hedge fund literature. In particular some of these breaks are associated with changes in Federal Reserve's interest rate policy. I further find that contrary to the previous arguments in the CTA literature, the average CTA is able to deliver statistically significant as well as economically significant alpha. These results are particularly contingent on the strategy of the CTA fund, with systematic trend-following CTAs delivering statistically significant alpha in every sub-period whilst the alpha of discretionary CTAs is only significant in the last three years of data.

I further analyse the performance persistence across CTA strategies and find results to be contingent on the strategy of the CTA, time horizon employed and fund size. The model proposed by Berk and Green (2004) suggests that performance persistence among fund managers may be contingent on fund size. As investors chase good past performance, thereby increasing flows to those funds and as funds face capacity constraints, funds with above average past performance quickly reach optimal size, which results in reduced performance persistence. In the hedge fund literature Boyson (2008) and Teo (2010) find empirical evidence to support the Berk and Green (2004) model: performance persistence is driven by small funds. These results however are not relevant for fund of hedge funds. Fung et al. (2008) find a subset of fund of hedge funds that deliver superior performance which persists. However, this performance persistence quickly disappears with increased asset inflows. In this study, I show that contrary to the findings in the hedge fund literature, performance persistence of systematic CTAs is driven by large funds. However, results for discretionary CTAs are in line with the hedge fund literature, in that performance persistence is driven by small funds. Furthermore, I find performance persistence for systematic CTAs at annual horizons but not quarterly. In contrast, for discretionary CTAs, I find no long-term performance persistence but only evidence of short-term performance persistence. These results have important implications for investors: investors may improve their future performance by selecting large systematic CTAs with strong past performance. For discretionary CTAs, they should select small funds with good past performance. The fact that performance persistence for systematic CTAs is driven by large funds is an interesting result, particularly as it is contrary to previous conclusions in the hedge fund literature. Size may serve as a proxy for research and development that is required for a successful systematic CTA.

Developing and backtesting models requires substantive research which in turn requires that a fund has adequate capital to hire suitable researchers and purchase data. Thus large funds will have more resources dedicated to successful R&D.

There are several extensions for future research. Firstly it would be interesting to improve the factor model for discretionary CTAs since using the F-H (2004) model for these funds left a large proportion of variance unexplained. Secondly, it would be interesting to see if fund age as well as size has an effect on the performance persistence of systematic CTAs. In the survival model, fund age was not a significant variable, only fund size and fund flows. Boyson (2008), however, finds age influencing the performance persistence of hedge funds. Thirdly, I found some of the structural breaks to be related to interest rate policy. It would be interesting to examine the effect of macroeconomic variables on the performance of CTAs and this probably would relate to the wider issue of why do CTAs perform particularly well during market downturns and why have CTAs delivered disappointing performance in the last two years.

In the last part of this thesis, I examine the fund flow-performance relationship in the CTA industry. In doing so, I use both quarterly as well as annual data, although quarterly data is more suitable to the study of CTAs. I found that in the period 1994 to 2010, systematic CTAs received more inflows than discretionary funds, indicating that investors are able to discriminate between the two styles. Regarding the flow-performance relationship, I find that at a yearly horizon, past relative performance is linearly related to flows, however, at the quarterly horizon, this relationship becomes concave for discretionary funds and remains linear for systematic CTAs. Contrary, to the conclusions of Ding et al. (2009) in the hedge fund literature, this relationship is neither driven by Live or Dead funds nor by share restrictions. I further examine the effect of past fund flows on future performance persistence. Sorting on size and inflows in addition to past performance, I find evidence of long-term performance persistence for systematic CTAs but no evidence of short-term performance persistence. This is an interesting result for institutional investors that may be concerned with capacity constraints in the hedge fund and CTA industry. This suggests that the future long-term performance of systematic CTAs is unlikely to be hindered by large inflows from institutional investors.

In the final part of the thesis, I also address the issue of capacity constraints and smart money in the CTA literature. To the best of my knowledge, the hypothesis of either has not been extensively examined in the CTA literature. I test for the presence of capacity constraints in the CTA literature using two methodologies. My results imply that there are no statistically significant capacity constraints for systematic CTAs, but there may be some capacity constraints across discretionary funds: the lagged flows for discretionary CTAs have a negative and statistically significant coefficient, although it is not as large as for some hedge fund strategies reported in Naik, Ramadorai and Stromquist (2007). Similar to the conclusions of Baquero and Verbeek (2009) in the hedge fund literature, I find no evidence of smart money in the industry. Thus despite the fact that CTAs offer greater liquidity to investors than hedge funds, investors are not able to fully exploit this advantage: I find no significant difference in performance between funds with inflows and funds with outflows using several methodologies. There appears to be no smart money effect in the CTA industry. One caveat is that this study covers the period up to December 2010. A possible extension to this study would be to include the last two years of data over which time CTAs have continued to attract asset inflows.

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