Survival of Commodity Trading Advisors: Systematic vs. Discretionary CTAs.

Julia Arnold, Robert Kosowski, Paolo Zaffaroni[1]

Abstract: This study investigates the differences in mortality between systematic and discretionary Commodity Trading Advisors, CTAs, over 1994-2009 period, the longest horizon than any encompassed in the literature. This study shows that liquidation is not the same as failure in the CTA industry. New filters are proposed that allow to identify real failures among funds in the graveyard database. By reexamining the attrition rate, this study finds that the real failure rate is in fact 11.1% in the CTA industry lower than the average yearly attrition rate of 17.3%. Secondly this study proposes a new way to classify CTAs, mainly into systematic and discretionary funds and provides detailed analysis of their survival. Systematic CTAs are found to have higher median survival than discretionary, 12 years vs. 8 years. The effect of various covariates including several downside risk measures is investigated in predicting CTA failure. Controlling for performance, HWM, minimum investment, fund age, leverage and lockup, funds with higher downside risk measures have a higher hazard rate. Compared to the other downside risk measures, volatility of returns is less able to predict failure. Fund flows have significant and positive effect on the probability of survival, funds that receive larger inflows are able to survive longer than funds that do not. Finally larger systematic CTAs have the highest probability of survival.

Keywords: CTA failure, liquidation, median survival, attrition rate, downside risk, systematic, discretionary.

JEL Classification: G11, G12, C31

[1]Paolo Zaffaroni is at Imperial College Business School p.zaffaroni@imperial.ac.uk. Robert Kosowski is at Imperial College Business School and the Oxford-Man Institute of Quantitative Finance r.kosowski@imperial.ac.uk. Julia Arnold is at Imperial College Business School and Tuneinvest Ltd.

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.[2] 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 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

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

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.[3] Analyzing survival during the recent financial crisis is of particular interest to investors who have become ever more cautious investing in hedge funds. This study 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 crisis of 2008.[4] 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 report-

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

[4] 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."

ing 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 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%.[5] 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

[5]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.

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 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 the study 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.

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. We eliminate from our sample funds that report quarterly or gross returns, a total of 15 funds. We 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.[6] This leaves 696 live funds and 1750 defunct funds. We 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 we impose an additional filter in which we require funds to have at least 24 months of non-missing returns.

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, we had access to fund identities that allowed us to

[6]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.

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 us to segregate CTA funds into various strategies. We therefore used funds' self-reported strategy description in addition to BarclayHedge categories and hand collected information and are 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, we propose a different CTA style classification based on the one used in the industry.

Firstly, we 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. We separate options strategies into a separate group as we 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. Our final three main category classification therefore has systematic, discretionary and options CTAs. Our classification is in line with recent work of Kazemi and Li (2010) who break their CISDM database into systematic and discretionary CTAs. However, we 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.[7] 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. We have employed a more stringent approach to qualify the funds as being systematic, however, and this explains the lower figure in our study. Our 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. We also note that among systematic funds, trend-following is the most dominant strategy with 87% of the funds. The vast majority of trend-followers employ a medium-term frame in a variety of markets. We 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.

[7] 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.

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.[8] 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 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 we 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

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

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. We 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.

We found that our 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. We 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 we 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 we 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 we 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 our filtering we 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. We 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.

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. We 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.[9]

Methodology

Risk Measures

Standard Deviation. For each month starting January 1994, we 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 consid-

[9]See Jarque and Bera(1980).

ers deviation from the mean only when it is negative.

$$SEM \equiv \sqrt{E\{min[(R-\mu),0]^2\}}, \tag{1}$$

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).

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 $VaR(\alpha,\tau)$ 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:

$$Prob[\Delta\widetilde{P}(\Delta t, \Delta\tilde{x}) > VaR] = 1 - \alpha, \tag{2}$$

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:

$$VaR\_Normal(\alpha) = -(\mu + z(\alpha) \times \sigma) \tag{3}$$

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.

$$\Omega(\alpha) = z(\alpha) + \frac{1}{6}(z(\alpha)^2 - 1)S + \frac{1}{24}(z(\alpha)^3 - 3z(\alpha))K - \frac{1}{36}(2z(\alpha)^3 - 5z(\alpha))S^2 \tag{4}$$

$$VaR\_CF(\alpha) = -(\mu + \Omega(\alpha) \times \sigma) \tag{5}$$

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:

$$\begin{aligned} ES_t(\alpha,\tau) &= -E_t\left[R_{t+\tau}|R_{t+\tau} \leq -VaR_t(\alpha,\tau)\right] \\ &= -\frac{\int\limits_{v=-\infty}^{-VaR_t(\alpha,t)} v f_{R,t}(v)dv}{F_{R,t}[-VaR_t(\alpha,\tau)]} \\ &= -\frac{\int\limits_{v=-\infty}^{-VaR_t(\alpha,t)} v f_{R,t}(v)dv}{\alpha} \end{aligned} \tag{6}$$

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, $F^{-}1_{R,t}$, 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:

$$TR_t(\alpha, \tau) = \sqrt{E_t[(R_{t+\tau} - E_t(R_{t+\tau}))^2 | R_{t+\tau} \leq -VaR_t(\alpha, \tau)]} \tag{7}$$

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 - we also calculate drawdown relative to annualized standard deviation. Annualized standard deviation is given by:

$$St.Dev.Annualised = \left(\sqrt{\left(\frac{\sum_{i=1}^{N} (R_i - \mu_R)^2}{N-1} \right)} \times 12 \right)^{\frac{1}{2}} \tag{8}$$

The proportion is calculated as:

$$= \frac{Max.Drawdown}{Std.Dev.Annuliased} \tag{9}$$

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

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:

$$F(t) = Pr(T \leq t) \tag{10}$$

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:

$$S(t) = 1 - F(t) = Pr(T > t) \tag{11}$$

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)*:

$$f(t) = \lim_{\Delta t \to 0} \frac{P(t \leq T \leq t + \Delta t)}{\Delta t} = \frac{\partial F(t)}{\partial t} = -\frac{\partial S(t)}{\partial t} \tag{12}$$

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.

$$f(t) \geq 0 \tag{13}$$

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:

$$\begin{aligned} h(t) &= \lim_{\Delta t \to 0} \frac{P(t \leq T < t + \Delta t | T \geq t)}{\Delta t} \\ &= \lim_{\Delta t \to 0} \frac{F(t + \Delta t) - F(t)}{\Delta t S(t)} = \frac{f(t)}{S(t)} = \frac{-dlnS(t)}{dt} \end{aligned} \tag{14}$$

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:

$$h(t) \geq 0 \tag{15}$$

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:

$$\begin{aligned} h(t) &= \frac{f(t)}{S(t)} \\ &= \frac{f(t)}{1 - F(t)} \\ &= \frac{-\partial[1 - F(t)]/\partial t}{\partial t} \\ &= \frac{\partial{-ln}[1 - F(t)]}{\partial t} \end{aligned} \tag{16}$$

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

$$\begin{aligned} \int_0^t h(u)du &= -ln[1 - F(t)]|_0^t \\ &= -ln[S(t)] \end{aligned} \tag{17}$$

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

$$\begin{aligned} S(t) &= exp\left(-\int_0^t h(u)du\right) \\ &= exp[-H(t)] \end{aligned} \tag{18}$$

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:

$$n_i = \sum_{j \geq i}^{k} (m_j + d_j) \tag{19}$$

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:

$$S(t) = \prod_{j|t_j<t} \left(1 - \frac{d_j}{n_j}\right) \tag{20}$$

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.

$$\hat{H}t_j = \sum_{j|t_j<t} \left(\frac{d_j}{n_j} \right) \tag{21}$$

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:

$$\lambda_i(t; z_i) = \lambda_0(t) e^{z_i^T \beta}, \tag{22}$$

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.[10]

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 Grego-

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

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

$$\lambda_j(t;\beta_j, Z(t)) = \lambda_{j0}(t)e^{z(t)^T\beta_j} \tag{23}$$

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* - we 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.

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

Empirical Results

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. Equally, Joenvaara et al. (2012) argue that the choice of the database can greatly influence the attrition results. They find that BarclayHedge has the highest coverage of the defunct funds and thus greater attrition rate relative to other databases.

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).

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.[11] 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

[11] 99 out of 2446 funds are self selected.

years, which has a downward impact on the median survival of all exits compared to liquidated funds only. This demonstrates that funds close fairly 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.[12] 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

[12]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.

earlier finding of Table 1.5 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 Gregoriou 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,[13] 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 significant 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,

[13] 53 months, from Panel A in Table VII

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.

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,[14] standard deviation of AUM over entire life of the fund, whether the fund has a hurdle rate, employs leverage, 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.[15] 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

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

[15] 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.

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 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 we 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, we 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. We also introduce another variable, asset flow, Flow(t). Following Agarwal, Daniel and Naik (2009) monthly flow is defined as:

$$DollarFlow_{i,m} = AUM_{i,m} - AUM_{i,m-1}\left(1 + Return_{i,m}\right) \tag{24}$$

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

$$Flow_{i,m} = \frac{DollarFlow_{i,m}}{AUM_{i,m-1}} \tag{25}$$

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.[16] 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 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

[16] 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.

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.

Robustness Checks

In unreported results we test to see if our 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.

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. Our 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.

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: **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 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 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 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 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 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 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 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 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 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 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 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 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 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 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 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^2_1)	308.74***		311.86***		323.37	
Global Ph Wald test	26.39		26.49		37.78	

Figure 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.

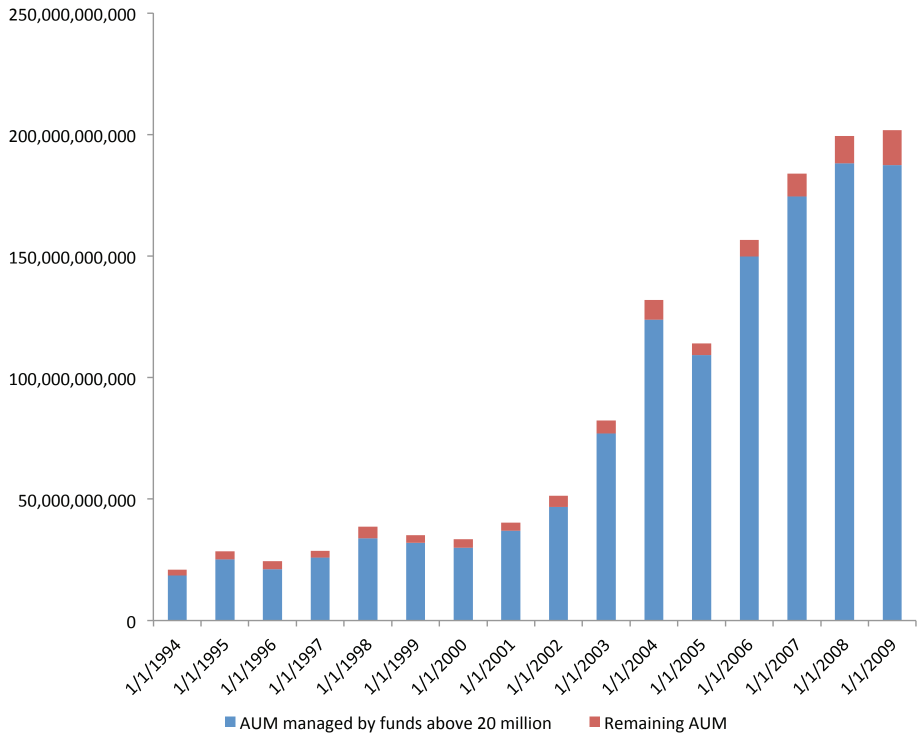


Figure 2: **Failed Fund with Small AUM**

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.

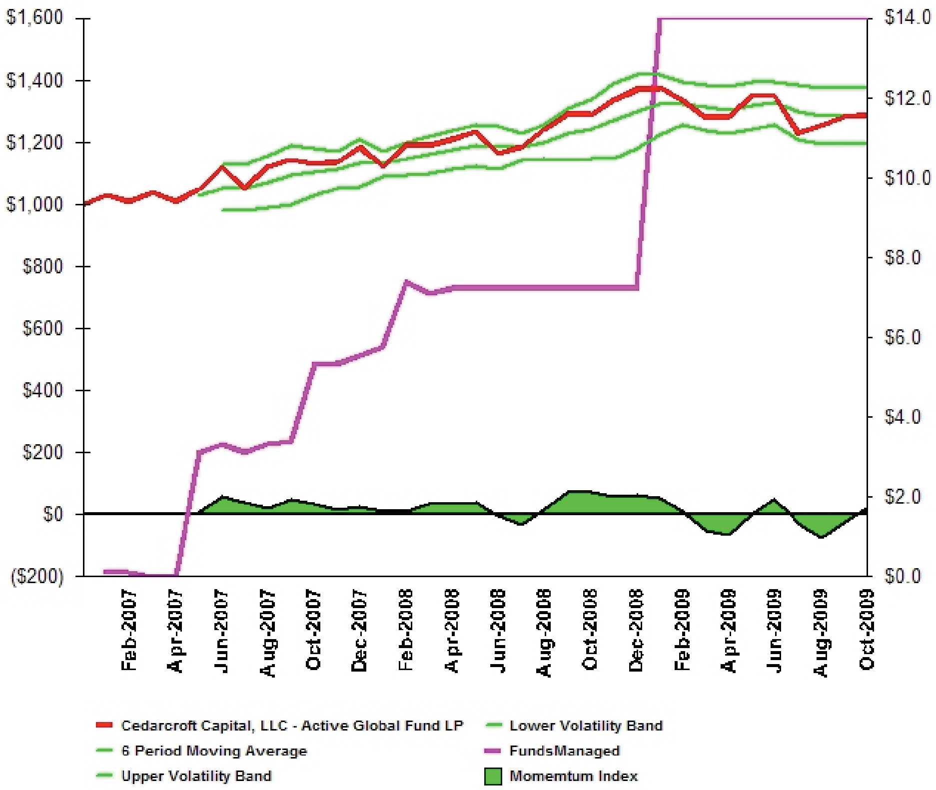


Figure 3: **Fund With Lost Assets More Than 12 Months Before End of Data**
Figure 1.3 shows VAMI and AUM for a fund whose assets dropped prior to 12 months before the end of data. Such a fund would not be caught by Liang and Park's (2010) filter. Source: PerTrac Analytical Platform.

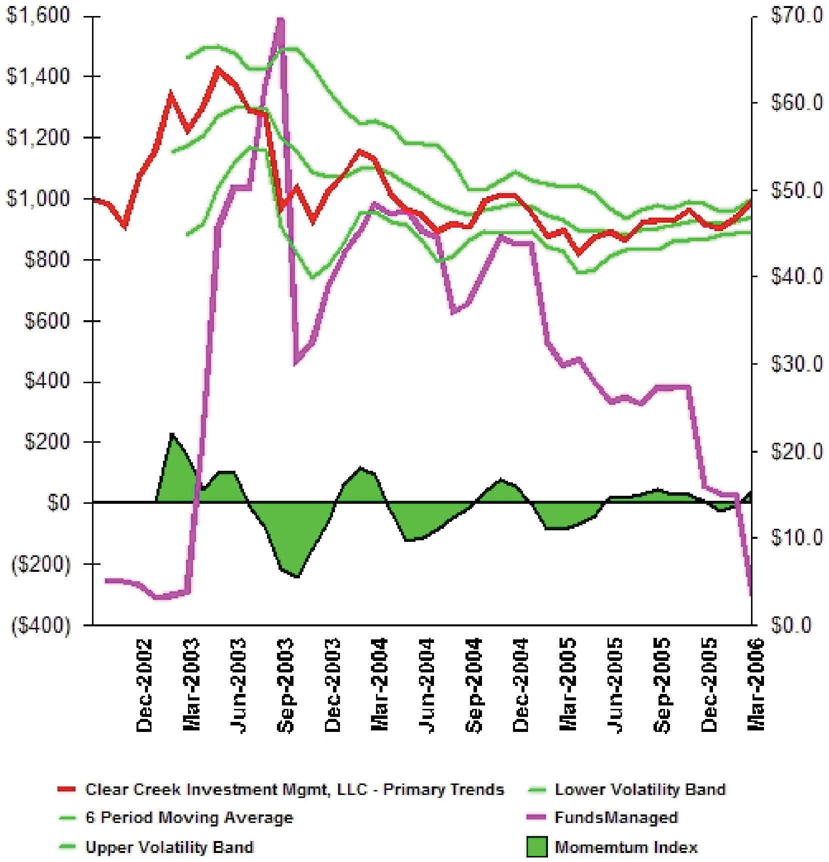


Figure 4: **Fund With Positive Average Return in the Last Six Months**
Figure 1.4 shows VAMI and AUM for a fund which experienced a large drawdown of 78.24% and a loss of assets yet in the last six months prior to termination its average return was positive. Such a fund would not be caught by Liang and Park's (2010) filter. Source: PerTrac Analytical Platform.

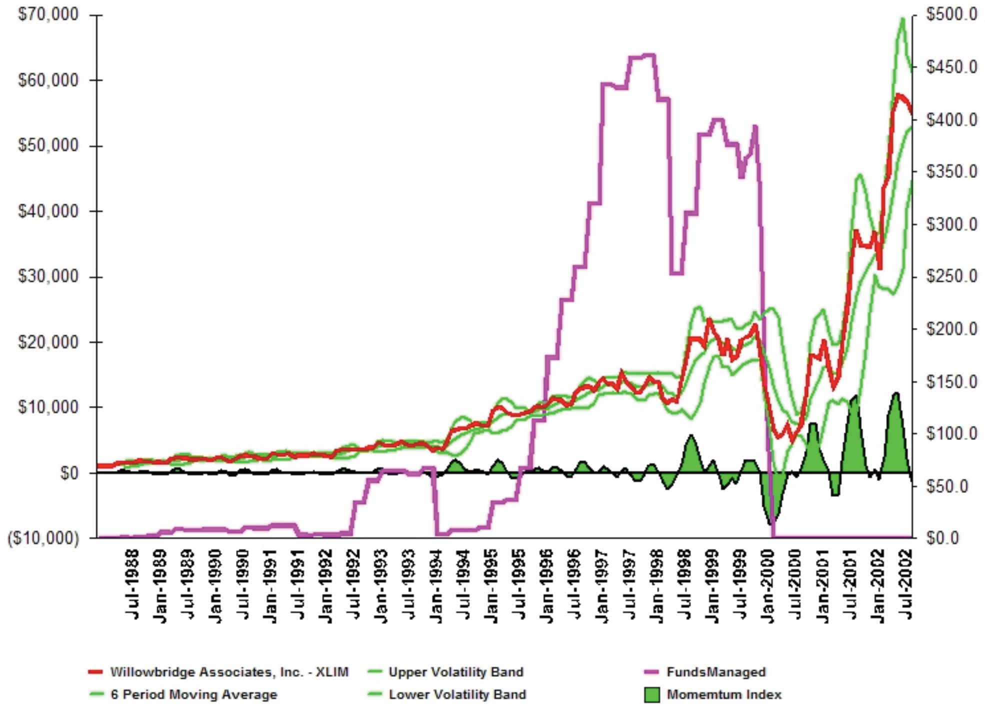
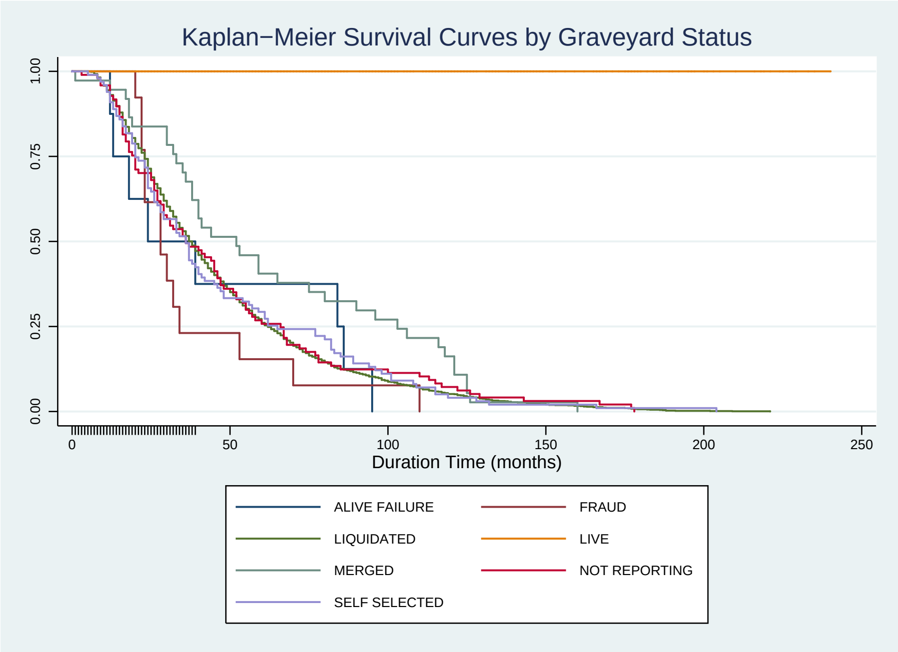


Figure 5: **Non-Parametric Survival and Hazard Curves**

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



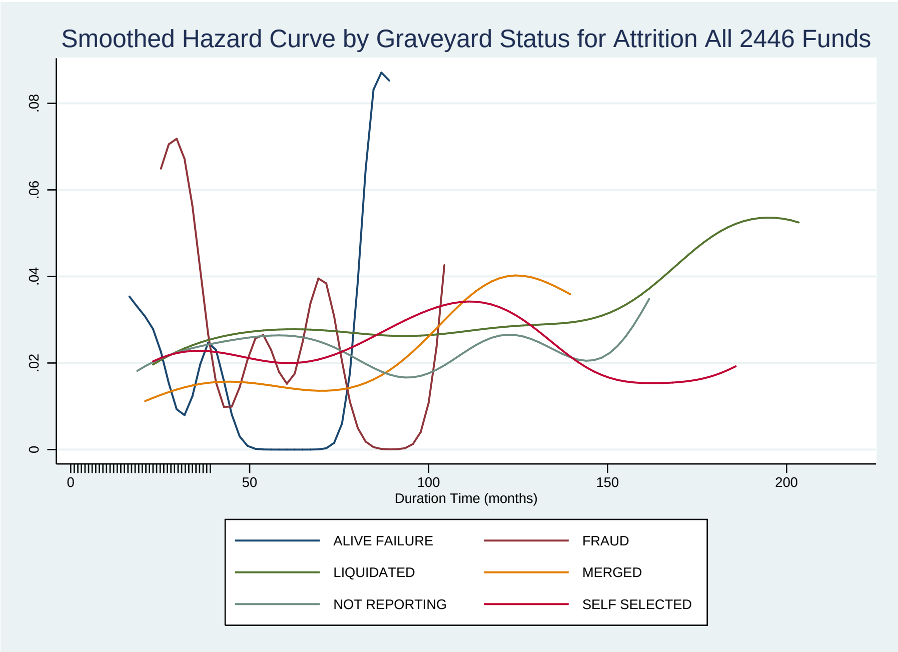
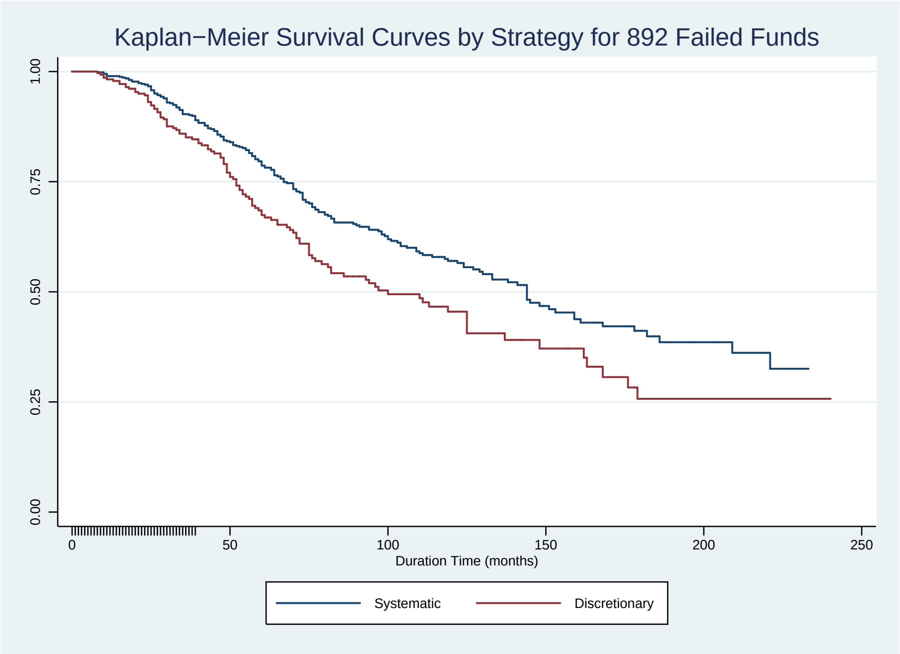


Figure 6: **Non-Parametric Survival and Hazard Curves**
Figure 1.6 shows survival and hazard curves for 892 funds filtered by dynamic AUM. The graphs show survival and hazard curves of systematic and discretionary for failed funds.



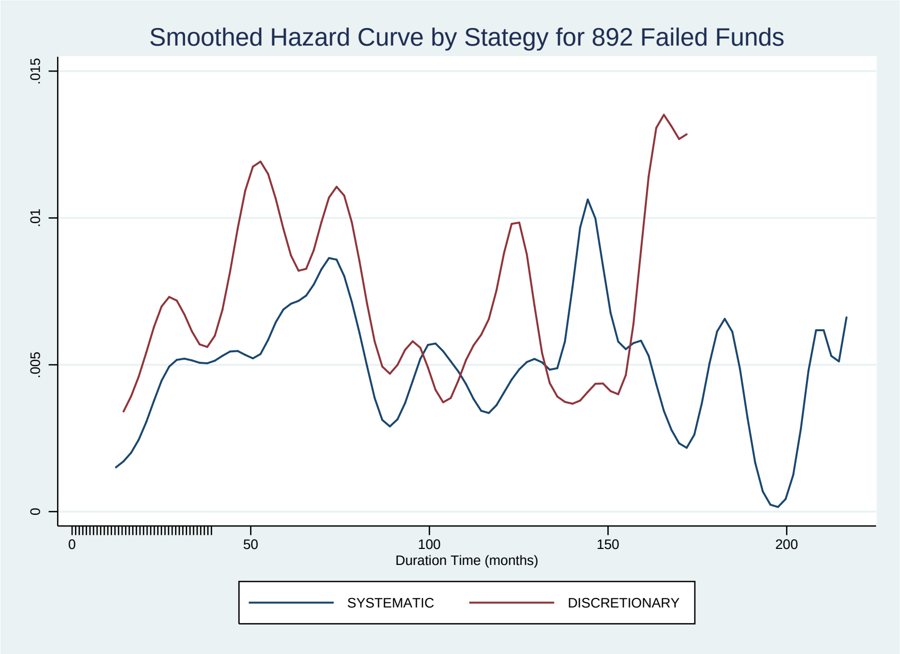
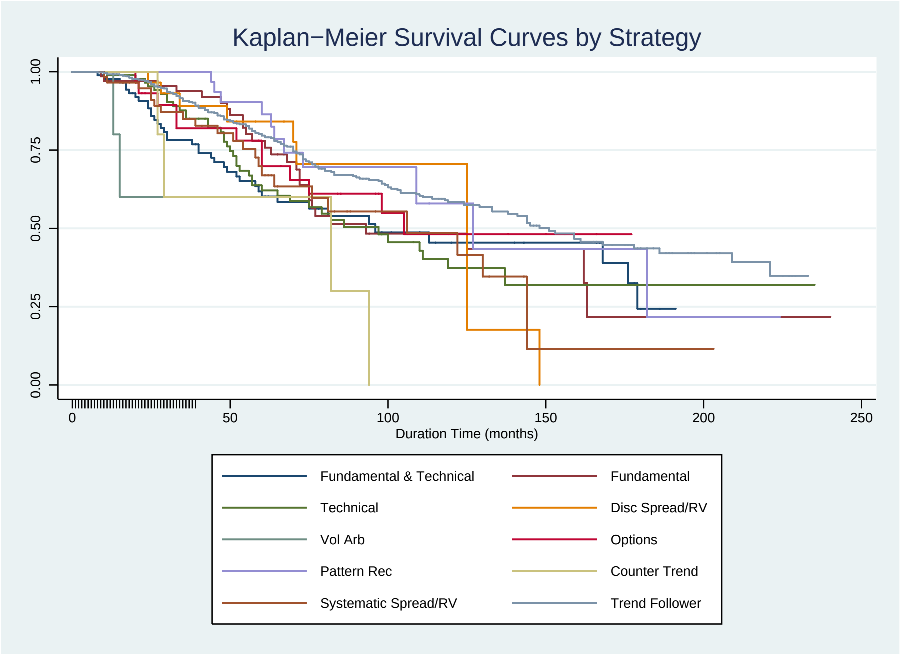
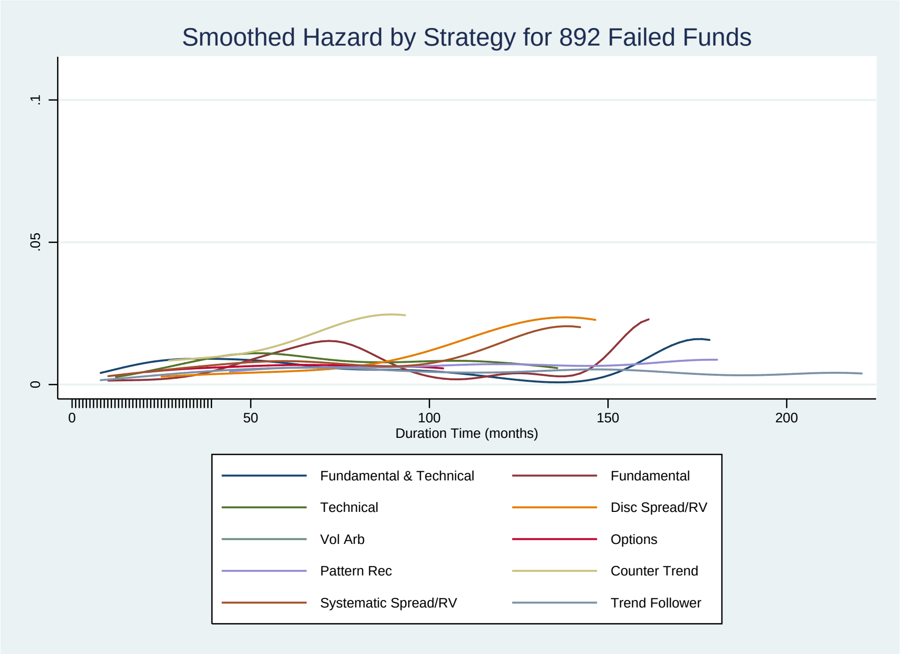


Figure 7: **Non-Parametric Survival and Hazard Curves**
Figure 1.7 shows survival and hazard curves for 892 funds filtered by dynamic AUM. The graphs show survival and hazard curves for failed funds across sub-strategies.





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