Essays on hedge funds, operational risk, and commodity trading advisors

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DEDICATION

This thesis is dedicated to the graduate students of McGill University.

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ABSTRACT

Hedge funds report performance information voluntarily. When they stop reporting they are transferred from the "live" pool of funds to the "defunct" pool. Consequently, liquidated funds constitute a subset of the defunct pool. I present models of hedge fund survival, attrition, and survivorship bias based on liquidation alone. This refines estimates of predictor variables in models of survival, leads to attrition rates of hedge funds to be roughly one half those previously thought, and produces larger estimates of survivorship bias. Survival models based on liquidated funds only, lead to an increase in survival time of 50 to 100 percent relative to survival based on all defunct funds.

In addition to refining estimates of survival time, it is useful to examine how the double fee structure of hedge funds and Commodity Trading Advisors (CTA) affects the incentives of their managers. Young CTAs are usually very small – they hold few financial assets – and may not meet their operating expenses with their management fee alone, so their incentive is to take on risk and post good returns. As they grow, their incentive to take on risk diminishes. CTAs in their fifth year diminish their volatility by 25 percent relative to their first year, and diminish returns by 70 percent. We find CTAs to behave more like indexers as they grow, concerned with more with capital preservation than asset management.

Operational risk is a major cause of hedge fund and CTA liquidation. In the banking industry, regulators have called upon institutions to develop models for measuring capital charge for operational losses, and to subject these models to stress testing. Losses are found to be inversely related to GDP growth, and positively related to unemployment. Since losses are thus cyclical, one way to stress test models is to calculate capital charge during good and bad economic regimes. We find loss distributions to have thicker tails during bad regimes. One implication is that banks will likely need to increase their capital charge when economic conditions deteriorate.

ABRÉGÉ

Les fonds de couverture déclarent leur performance de leur propre initiative. Lorsqu'ils cessent de le faire, ils passent du groupe des fonds «vivants» à celui des fonds «morts». Les fond liquidés ne constituent donc qu'un sous-ensemble des fonds morts. Je me propose d'isoler les fond liquidés et de présenter plusieurs modèles de survie, d'attrition et de biais de survie qui tiennent compte uniquement des fonds liquidés. On obtient ainsi les estimations plus fines des variables prédictives, d'où il s'ensuit des taux d'attrition inférieurs de moitié aux prévisions initiales et un biais de survie plus important. Les modèles de survie basés sur la liquidation augmentent la durée de survie de 50 à 100 pour cent par rapport aux modèles basés sur l'ensemble du groupe des fonds morts.

Le Commodity Trading Advisor (CTA), ou conseiller en échange des commodités, perçoit deux types d'honoraires, à savoir une indemnité de gestion fixe sur les actifs, et une prime qui ne lui est versée que s'il dégage un bénefice net. Les jeunes CTA ont peu d'actifs et ne parviennent pas toujours à couvrir leurs frais de gestion uniquement avec l'indemnité fixe, ce qui les incite à prendre des risques pour pouvoir afficher de bons résultats. Lorsque leurs actifs prennent de l'ampleur, cette incitatif diminue. Dans leur cinquième année d'exercice, les CTA diminuent leur volatilité de 25 pour cent par rapport à leur première année, et leur rendement est réduit de 70 pour cent. Lorsque leur actifs augmentent, les CTAs se comportent de plus en plus comme des

indexeurs, et se préoccupent davantage de la préservation de leur capital que de la gestion des actifs.

Le risqure opérationnel est une cause importante de liquidation des fonds de couverture et des CTAs. Dans le secteur banquaire, les organismes de réglementation ont demandé aux banques de mettre au point des modèles de réserve de capital pour les pertes opérationnelles, et de soumettre ces modèles à des tests de tension. Les pertes varient avec le taux de chômage, mais varient en fonction inverse de la croissance du PIB. Etant donné qu'elles sont cycliques, je propose un test de tension basé sur le climat macroéconomique. Les queues des distributions des pertes st plus étendues lorsque ces pertes sont contractés pendant des périodes défavorables, ce qui implique que les banque devraient augmenter leur réserve lorsque la conjoncture se détériore.

CONTRIBUTION OF AUTHORS

The first chapter of this thesis was written entirely by Fabrice Rouah.

The second chapter is a joint collaboration between Fabrice Rouah and Susan Christoffersen, Assistant Professor of Finance, Desautels Faculty of Management, McGill University. Fabrice Rouah performed all the data management and data analyses that make up the chapter, and did all the writing. Fabrice Rouah and Susan Christoffersen developed the main research ideas behind the chapter, decided on which tables should be included, and discussed revisions of the chapter.

The third chapter is a joint collaboration between Fabrice Rouah, Susan Christoffersen, and René Garcia, Professor, Department of Economics, Université de Montréal. Fabrice Rouah performed all the data management and data analyses that make up the chapter, and did all the writing. Fabrice Rouah, Susan Christoffersen and René Garcia developed the main research ideas behind the chapter, decided on which tables should be included, and discussed revisions of the chapter.

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LIST OF ABBREVIATIONS

AMA	Advanced Measurement Approach
AUM	Assets Under Management
BCBS	Basel Committee on Banking Supervision
BTOP	Barclay BTOP 50 CTA Index
CaR	Capital at Risk
CISDM	Center for International Securities and Derivatives Markets
CTA	Commodity Trading Advisor
CRSP	Center for Research in Security Prices
GDP	Gross Domestic Product
GSCI	Goldman Sachs Commodity Index
HFNet	HedgeFund.Net CTA Index
HFR	Hedge Fund Research, Inc.
HML	High Minus Low portfolio
LAB	Lehmann Brothers Aggregate Bond Index
LDA	Loss Distribution Approach
NBER	National Bureau of Economic Research
PH	Proportional Hazards
SA	Standardized Approach
SAI	Statement of Additional Information
SMB	Small Minus Big portfolio
SP500	Standard and Poor's 500 Index
UMD	Up Minus Down portfolio

CHAPTER 1
INTRODUCTION

In this thesis we present essays on hedge funds, Commodity Trading Advisors (CTA), and operational risk. The amount of money being allocated to hedge funds and CTAs is growing substantially, and much of this new money comes from institutional investors. Their enthusiasm has been dampened by well-publicized hedge fund liquidations and the large capital losses that often accompany these liquidations. Notwithstanding the capital erosion that often precedes liquidation, liquidation itself is a costly event because of legal costs, low liquidity, predatory trading and forced sale of assets at "fire sale" prices (Brunnermeier and Pedersen, 2005).

The outlook for the hedge fund and CTA industry, however, remains bullish. Investors are planning their investments into hedge funds and CTAs on a long-term basis, and are seeking funds that will not liquidate prematurely. Survival analysis can help investors select funds with characteristics associated with an extended lifetime, and avoid those that are likely to liquidate. Hedge funds with longevity can ease illiquidity concerns, namely long lock-up periods on new capital and infrequent redemption. To address these issues, in Chapter 2 of this thesis we present models that allow investors to estimate the risk of hedge fund liquidation, and to identify funds with longevity.

Fung and Hsieh (2002) point out that many funds exiting databases have not liquidated, but have simply stopped reporting to the database vendor, for a variety of reasons. Many academic studies, however, have treated all exited funds as liquidated. The aggregation of exits into a single group can lead to at least five distortions. First, the effect of predictor variables on survival becomes blurred; second, it leads to distorted estimates of survival time; third, it does not allow for survival time to be defined in terms of liquidation only

– the only exit type that is of concern to investors (Baquero, ter Horst, and Verbeek, 2005); fourth, it may produce mortality estimates that are artificially inflated; finally, it may underestimate survivorship bias. In Chapter 2, we present models that correct for these distortions.

As done by Boyson (2002), we treat variables whose values change over time as time dependent variables, rather than as fixed variables as is done in existing studies. Indeed, the former approach is an *ex-ante* measure, but the latter is an *ex-post* measure since variable values can only be determined after a fund has exited, which introduces lookback bias. In existing studies, performance is typically measured one or two years prior to the fund exiting. Time dependent variables, on the other hand, allow the performance of a group of hedge funds to be compared at each point in time, rather than at the end of their lifetimes.

By avoiding hedge funds that are likely to liquidate, investors can avoid the large capital losses that often accompany liquidation. In order for this to be done accurately, liquidation must be separated from the other exit types. In Chapter 2 we apply a competing risks survival model, and multinomial regression – both of which allow for different exit types – and estimate the attrition rate of hedge funds due to each exit. Finally, we use a Weibull model under competing risks to estimate the median survival time of funds, based on values of predictor variables.

It has often been pointed out that each category of hedge fund is a separate investment strategy, and that ideally, each category should be analyzed separately. In Chapter 3, we examine the relationship between fees, size, and performance in CTAs, a class of hedge fund that deal exclusively in managed futures and that tend to be small in size. CTAs earn their compensation from two sources, a management fee, which is asset-dependent, and an incentive fee, which is performance-dependent. These two fees are meant to act in tandem. The management fee assures that the CTA will earn compensation during hard times when positive returns are not realized, assuring the CTA's survival during bad economic conditions or during a run of bad luck. The incentive fee, on the other hand, rewards the manager for good performance. Hence, there are three ways by which the CTA can earn high compensation, by posting good performance, by amassing a large asset base, or both. In this thesis we argue that as CTAs grow, they earn proportionately more of their compensation from the management fee, and less from the incentive fee. Hence the incentive to post good returns diminishes, and they become more passive investors and adopt strategies that increasingly resemble indexing strategies.

Incentive contracts are designed to mitigate the agency problems that can arise when principals are entrusted to manage large sums of money on behalf of their clients. These contracts are popular in the alternative asset industry, since the absence of regulation and infrequent transparency implies that direct monitoring of manager activities is costly and often not feasible. Incentive contracts are thus employed by a large number of hedge funds, venture capital funds, private equity funds, and CTAs. Managers typically earn their compensation from a management fee defined as a percentage of assets under management (AUM), and an incentive fee defined as a percentage of profits, often in excess of a hurdle rate. These fees are usually two and twenty percent, respectively. The incentive contract often stipulates a highwater mark, according to which the incentive fee is not charged until previous losses have been recuperated. By motivating the manager to generate profits, the incentive fee is meant to align the interest of the manager with those of the clients. It motivates the manager to post good performance, because in that case the manager earns much more compensation than from the management fee alone. This is particularly true given the relatively small asset base that CTAs typically manage.

Incentive contracts are not without problems, however, especially when coupled with a management fee on AUM. Golec (1993) argues that small CTAs with a short-term investment horizon may simply take on riskier positions to bolster future returns. CTAs may start out with a small asset base, and apply high-risk strategies to post good returns, which will attract additional capital. Larger CTAs, on the other hand, seek to reduce risk to prevent capital outflows and maintain their asset base. This increased risk aversion, however, may result in decreased performance. Hence, the two sources of fees charged by CTAs provide opposite incentives. Small, generally young CTAs rely on their incentive fee and take on risk to boost performance and increase their asset base, while older, larger CTAs depend on their management fee and become risk averse as they grow. The findings of this thesis support these views. In particular, we find a relationship between fees, size, returns, and risk. Young, small CTAs need to earn compensation from their incentive fee because they are too small to survive on their management fee alone. Consequently, they tend to take on higher risk and post good returns. Older, well-established large CTAs derive a large proportion of their compensation from management fees, and have lower returns and volatility. They become more passive investors and behave more like indexers as they age.

Unlike hedge funds and CTAs, mutual funds charge management fees and load fees that are paid when entering and exiting the fund. Mutual funds do not usually stipulate incentive contracts because these contracts are often linked to excessive risk-taking by managers (Elton, Gruber, and Blake, 2003). Furthermore, since they are heavily regulated and must adhere to federal and state legislation, it is not crucial for investors to monitor the activities of mutual fund managers directly. Investors can count on regulatory authorities and internal safeguards to monitor them on their behalf. These funds have an interest to grow their asset base so that the compensation earned from their management fee can be as high as possible. Hence, mutual fund managers are "asset gatherers" since they earn most of their compensation from management fees (Chevalier and Ellison, 1997). CTAs, on the other hand, are "asset managers" who must generate profits in order to collect the additional incentive fee. The results of Chapter 3 show that this is especially true for young CTAs with a small asset base. We find CTAs with high incentive fees to hold an average of \$4.4M in AUM, while those with low incentive fees, to hold an average of \$5.1 M in AUM. CTAs with high management fees held an average of \$5.2M in AUM, while those with low management fees held an average of \$3.1 M in AUM.

While incentive fees exist in the mutual fund industry, these are not directly observable outside of the Statement of Additional Information (SAI) posted by mutual funds. The SAI specifies the structure of any incentive-based bonus awarded to the fund managers, and this bonus is usually linked to the performance of the fund and/or its Morningstar or other peer-group ranking. In CTA databases, the management and incentive fees are both directly observable. Examining both fees and their relationship to such variables as size, age, and performance, can help understand the incentives driving CTA managers in particular, and money managers in general. For example, Chevalier and Ellison (1999) show a negative relationship between age and performance. The managers of young funds wish to build a track record and chase high returns to attract capital inflows, while managers of older, established funds are more risk averse and protective of their reputation. In Chapter 3 we argue that the desire to build a large asset base is also driven by the desire to earn a large part of fees from management fees. In so doing, managers reduce the need to post stellar performance, and become more risk averse and more concerned about capital preservation. In brief, the evolution of fees is a complementary explanation of the size-performance relationship, in addition to reputation effects, career concerns, and risk aversion.

Survival analysis can help explain why hedge funds fail, and remuneration contracts can help disentangle the different incentives hedge fund and CTA managers are subject to. Liquidation can be a voluntary event, since it is sometimes optimal for a manager falling below the highwater mark when economic conditions deteriorate, or during a run of bad luck, to simply liquidate assets and start a new fund. Liquidation can also be the result of operational events (Bank of New York, 2006). Unfortunately, hedge fund and CTA databases do not include the reason behind liquidation, so it is not possible to identify which fund liquidations are voluntary, and which are due to operational failures. It is possible, however, to examine operational risk in the banking sector.

In Chapter 4, we evaluate how losses from operational events depend on the economic climate during which the losses were incurred. Under the 1998 Basel II Capital Accord, international banks will need to provide estimates of their capital charge for operational risk, as they are for market risk or credit risk. The definition of operational risk has evolved from a vague description of all risks that are neither market risk nor credit risk, to a more precise definition as "the risk of direct or indirect loss resulting from inadequate or failed internal processes, people and systems or from external events" (Basel Committee on Banking Supervision (BCBS), 2001). Losses arising from operational risk are classified as arising from seven possible event types. Losses incurred by banks are further classified as originating from one of eight possible business lines relating to banking activities. The BCBS has called upon the banking and academic communities to develop models to measure the capital charge that international banks should hold as a reserve to cover operational losses.

Consequently, much of the research into operational risk has focused on models for capital charge. However, no study measures how operational losses depend on the prevailing economic conditions under which international banks and other large financial firms operate. If such a dependence exists, it would imply a dependence between capital charge and economic conditions, so that firms would need to adjust their capital charge when economic conditions change. We address this issue, and find that losses are more severe when times are bad.

We measure the link between losses and the economic conditions under which losses were incurred, and show that this link is present across the major lines of business of international banks. We also show that the tails of distribution of operational losses are thicker for losses sustained during bad economic times, and propose and test several hypotheses linking operational losses to economic conditions. We analyze losses experienced by U.S. firms, losses experienced by U.S. financial firms, including banks, brokerage firms, insurance companies, mutual funds and other investment companies, and losses experienced by international banks. We propose that when individuals experience financial distress, such as the loss of a job, a decrease in the value of their investment portfolios, a bankruptcy or a loss of savings, they are more likely to engage in fraudulent behaviour. To test this hypothesis, we fit a series of linear regression models to yearly losses, using economic factors as explanatory variables.

During periods of bad economic conditions, firms may not have the resources to adequately monitor their operations, upgrade their equipment, or implement safety programs, which would increase losses from damage to physical assets, from system failures, and from workplace accidents. They may also impose large layoffs and work stoppages, opening the possibility of losses from lawsuits brought on by employees or by unions. The economic variables affecting each type of loss may not be the same. For example, GDP may help explain losses due to inadequate firm resources, while the unemployment rate may help explain losses due to lawsuits for unjust layoffs and firings.

To test the relationship between losses and economic variables, in Chapter 4 we fit a linear regression model on scaled losses with GDP growth and unemployment as predictor variables. We also wish to control for whether or not a loss arises from fraud. For technological reasons, it may be difficult for outsiders to commit fraud on financial firms. Hence, financial firms may be more at risk of internal fraud than external fraud. For this reason, we include in the regressions dummy variables corresponding to internal fraud and external fraud. The effect of macroeconomic variables on losses could differ depending on the nature of the loss. For example, individuals might be more inclined to commit internal fraud on financial firms when economic conditions deteriorate. Hence, in the regressions we include interaction terms between the loss type, and the macroeconomic condition.

The dependence of operational losses on prevailing economic conditions raises the possibility that losses could be contagious across firms, or across the different business lines of the same firm. Contagion is reflected in the Standardized Approach (SA) proposed by the BCBS, which assumes perfect dependence between the lines of business operated by banks. Perfect dependence produces the largest possible capital charge, since it assumes that losses in one line will lead to similar losses in the other lines through contagion. The BCBS has called upon the banking industry to propose models to estimate the dependence of losses across business lines. In particular, banks are encouraged to develop models that can identify less than perfect dependence and that can integrate this feature into capital charge calculations. Banks that can show decreased dependence will be rewarded with a reduced capital charge. If business lines are exposed to contagion, however, then dependence and capital charge would both increase when economic conditions decline.

While methods to model the dependencies of losses across business lines have been proposed in the literature, none has attempted to identify how these dependencies might change when economic conditions deteriorate and contagion sets in. Our next hypothesis is that these dependencies increase during periods of bad economic conditions so that reduced dependence is appropriate only during good economic times. We show that the increase in losses brought on by deteriorating economic conditions is present across most lines of business. If banks move to reduced-dependence models, then they cannot ignore how the performance of these models might be hampered during bad regimes.

The Loss Distribution Approach (LDA), which forms part of the Advanced Measurement Approach (AMA) proposed by the BIS, applies actuarial methods to model operational losses and calculate capital charge for operational risk, but does not specify how to adapt these methods to changing economic regimes. If losses are not the same across regimes, the parameters used to model the distribution of these losses would change. Consequently, estimates of capital charge produced by the LDA would not be the same in each regime. The results of Chapter 4 show that the percentiles of the distribution of operational losses are larger for losses experienced during bad times. This would impact LDA estimates of capital charge, which are often derived by simulating aggregate loss distributions with random frequency and severity. Hence, banks that calculate capital charge by using the LDA, rather than by using simpler methods such as the Basic Indicator Approach, must be aware that their capital charge estimates could be insufficient when economic conditions change for the worst.

CHAPTER 2

COMPETING RISKS IN HEDGE FUND LIFETIMES

Fabrice Rouah

2.1 Introduction

Hedge fund liquidation is often characterized by a substantial loss of investor capital, in addition to the legal and administrative costs that investors must bear following liquidation. To help investors avoid hedge funds likely to liquidate, liquidation must be properly identified as an outcome in models of hedge fund survival and mortality. Most studies on hedge fund failures, however, have failed to separate liquidated hedge funds from the general group of hedge funds that stop reporting to database vendors. In this chapter we present models that are based on liquidation alone, and produce estimates of hedge fund survival and mortality that are more refined than those previously encountered in the literature.

The results of this chapter can be summarized as follows. We find size and returns volatility to be much more important predictors of liquidation risk than of the other exit types, and the presence of a highwater mark to be strongly associated with liquidation. We find survivorship bias to be very high when only liquidated funds are used to define the pool of defunct funds. We also find attrition rates that are roughly one-half those obtained when all exits are used. Finally, we find that isolating liquidation leads to lifetimes that are roughly twice as long as those estimated when exits are aggregated.

2.2 Literature Review

In most studies, such as those by Brown, Goetzmann, and Ibbotson (1999), Fung and Hsieh (2000), Liang (2000, 2001), Barès, Gibson, and Gyger (2001), Edwards and Caglayan (2001), and Barry (2002), survivorship bias is estimated at 2 to 4% per year. Estimates of the attrition rate usually range from

5 to 15%, as found by Liang (2000, 2001), Barry (2002), Barès, Gibson, and Gyger (2001), and Baquero, ter Horst, and Verbeek (2005). Estimates of the fifty percent (median) survival time of hedge funds are also varied. Brown, Goetzmann, and Park (2001) estimate it to be 2.5 years, Amin and Kat (2003) to be 5.0 years, while Gregoriou (2002) and the Securities Exchange Commission (2003) each estimate it to be 5.5 years. Barès, Gibson, and Gyger (2001), however, estimate it at over 10 years. The estimate is high because that study used all funds in the Financial Risk Management (FRM) database up to 1999, and not only funds born after 1994, like most studies reviewed in this chapter.

Some authors have used probit regression to link hedge fund survival status (live versus defunct) to predictor variables. Liang (2000), Baquero, ter Horst, and Verbeek (2005), Brown, Goetzmann, and Park (2001), and Chan et al. (2005) find that young funds, funds with poor performance, with a small asset base, and with high leverage, are at increased risk of death. Brown, Goetzmann, and Park (2001), Gregoriou (2002), Baba and Goko (2006), and Boyson (2002) have applied the Cox proportional hazards model to hedge fund lifetimes, and have found essentially the same results.

Many of these studies have treated all exited hedge funds as a single group, which could mitigate the effect of predictor variables on survival. For example, funds closed to new investment may have good returns, while liquidated funds have poor returns. By aggregating these exits, the effect of returns on survival will tend to cancel out. Ackermann, McEnally, and Ravenscraft (1999), Boyson (2005), Jagannathan, Malakhov and Novikov (2006), and Baquero, ter Horst, and Verbeek (2005), consider liquidation as a separate outcome. Park (2007) defines a failure criteria based on negative returns and decreased assets for his survival analyses.

In this chapter we focus on hedge fund survival and mortality. We apply longitudinal and categorical models that isolate liquidation, and calculate mortality and survivorship bias due to liquidation only.

2.3 Data

We use 1,912 live funds and 648 defunct funds from the Hedge Fund Research, Inc. database (HFR), covering the period January 1994 to December 2003. In the HFR database, funds exit for three reasons (1) they are liquidated, (2) they are closed to new investors, or (3) they have stopped reporting to HFR. Liang (2000) shows that defunct funds are under-represented in the HFR database relative to the TASS/Tremont database. To ensure that our results are not sensitive to the choice of data (HFR), as a robustness check we run analyses using TASS data over the same time period. We examine the following hedge fund variables to determine which are useful predictors of fund liquidation:

- Monthly return and assets under management (AUM) are treated as time dependent predictor variables. At each point of a hedge fund's lifetime, the mean and standard deviation of these variables twelve months prior to the point is used.

- Management and incentive fee, minimum investment, hurdle rate, high-water mark. Databases usually include only a single value of these variables, so we treat them as fixed.

- In our cross-sectional models we also include the fund's age as a predictor variable.

Table 2.1 presents the number of live and defunct funds experiencing each exit type, and the mean and standard deviation of their returns over the 1994 to 2003 period, and during the last twelve and six months preceding exit. During the last twelve and six months, defunct funds have returns that are substantially lower than those of live funds, but much of this difference can be attributed to liquidated funds. Among the defunct group, only liquidated funds suffer a drop in assets during the last year of life. The three groups of exiting funds are not homogeneous, but it is difficult to infer from this data why hedge funds exit since these classifications are self-reported and cannot be refined. Still, it appears that liquidated funds fare much worse than other exited funds, especially during the latter stages of life.

Figure 2.1 illustrates the capital evolution of the hedge funds in our sample, during their last 48 months of observation. Live funds perform well and their asset base nearly doubles over the last four years of observation. The assets held by funds closed to new investment and funds no longer reporting also grow, but not nearly as dramatically. Only liquidated funds experience capital erosion. This graph suggests that investors are likely to experience capital losses if they allocate money to funds that eventually liquidate. It also indicates that the capital evolution of the exited pool of funds is not homogenous.

2.4 Methods and Results

In this section we describe and estimate the competing risks model, the multinomial logit model, hedge fund attrition rates and survivorship bias, and the Weibull model.

2.4.1 Competing Risks Survival Model

We define the lifetime of a hedge fund as a non-negative random variable, T, and estimate the survival function $S(t)$ and the hazard function $\lambda(t)$. We apply the Cox proportional hazards (PH) model with time dependent predictor variables under competing risks. In this model, each of the three exits is treated as a separate failure type. For the jth exit type ($j = 1, 2, 3$) the model assumes a hazard function of the form

$$\lambda_j\left(t;\beta_j,Z(t)\right)=\lambda_{j0}(t)\exp\left(Z(t)^T\beta_j\right),$$

where $Z(t)$ is a vector of predictor variables (some of which are time dependent), and where for each exit type, $\lambda_{j0}(t)$ is a latent baseline hazard function and β_j is a vector of coefficients (Kalbfleisch and Prentice, 2002). This model is a generalization of the Cox PH model with a single exit, with hazard function given by $\lambda\left(t;\beta,Z(t)\right)=\lambda_0(t)\exp\left(Z(t)^T\beta\right)$.

For each predictor variable the Cox model produces a hazard ratio (HR), which represents the change in the hazard rate of the fund brought on by the variable. When $HR>1$ the variable increases the hazard (decreases survival), and when $HR<1$ the opposite is true. The percent change in the hazard rate of the fund due to the variable is given by $(HR-1)\times 100\%$. The Cox model does not usually provide estimates of survival time, only of the impact of predictor variables on survival, via the hazard function. Later in this chapter we present a model that produces estimates of survival time, based on values of predictor variables.

2.4.2 Competing Risks in Hedge Fund Lifetimes

Table 2.1 indicates that the group of exited funds does not constitute a homogeneous group. Consequently, the effect of performance and size predictor variables on survival would become blurred if the exit types were aggregated. To correct for this possibility we fit the Cox PH model for each exit type separately in a competing risks framework. For comparison with existing studies, we also aggregate the exits and apply a conventional Cox model. To minimize backfill bias (Ackermann, McEnally, and Ravenscraft, 1999), we use only funds born on or after January 1st, 1994.

The results are presented in Table 2.2. The effect of many predictor variables is different when each exit type is treated separately, and the effect tends to cancel out when exits are combined. For example, the hazard ratio of 1.058 for all exits combined suggests that every \$100M increase in asset volatility increases the risk of death by 5.8%. In fact, the hazard ratio of 1.243 for liquidation indicates that the correct increase is 24.3%. Investors are therefore much more at risk of fund liquidation due to high asset volatility than suggested by the aggregated-exit model.

Examination of the other hazard ratios further illustrates how the effect of explanatory variables becomes blurred when exits are aggregated. Every one percent increase in monthly returns decreases the risk of all exits by 6.9% (obtained as $(0.931 - 1) \times 100\%$), but decreases the risk of liquidation by 9.6%. Investors are therefore more protected of liquidation by high returns than indicated by the aggregated-exit model. For funds closed to new investment, the effect of incentive fee is strongest, as is the effect of average assets under management. This is consistent with the argument of Fung and Hsieh (2002) that good managers can charge high incentive fees, build up their asset base, and close their funds when a target asset size is reached.

The results in Table 2.2 indicate also that high management fees are associated with a decreased risk of fund liquidation, which suggests that good managers can charge high management fees and still avoid liquidation. The highwater mark employed by some hedge funds, however, is associated with an increased risk of liquidation. This reflects the argument of Brown, Goetzmann, and Ibbotson (1999) and Liang (2000) that once losses are incurred, it is difficult for some managers to recuperate losses and attain their highwater mark. These managers may have no incentive to continue operating the fund, and may simply liquidate its assets (Scholes, 2004). This choice may even be optimal for investors, if the cost of liquidation is inferior to the cost of the extra compensation produced by the highwater mark.

In general, the hazard ratios for all exits in Table 2.2 are consistent with those encountered in studies that aggregate exits. For example, our estimate of 0.931 for returns is comparable to the value of 0.899 obtained by Gregoriou (2002), and our estimate of 0.881 for the management fee is very close to 0.879 obtained by Baba and Goko (2006). Our hazard ratio estimate of 0.977 for minimum investment is larger than 0.801 obtained by Gregoriou (2002). Our estimate, however, is not significant, so in this chapter fund size is better proxied by assets under management. Unfortunately, the agreement between our estimates and those encountered in the literature cannot be tested statistically. We also find that funds with a hurdle rate tend to survive longer, which suggests that skilled managers are confident enough to impose a hurdle on their performance fees.

The funds in our sample are subject to two types of censoring, (*i*) random censoring, since non-liquidated exited funds are censored at their exit date, and (*ii*) generalized type I censoring, since the dates of entry are staggered and censoring for funds surviving until the end of the study period occurs at a pre-determined date (December, 2003). By translating all staggered lifetimes to a common unique origin, we make the strong assumption of time homogeneity, according to which the calendar dates of inception and exit of a fund have no effect on its survival. To allow for time heterogeneity, we run the Cox PH model in Table 2.2 with two additional variables, corresponding to the year of inception and year of exit (results not shown). These variables are both highly significant, but their effects are artificial since the majority of our funds are censored (alive). The year of inception increases risk, but funds born later have shorter lifetimes simply because most have been censored at

December 2003. The year of exit decreases risk, but funds that die in later years naturally have longer lifetimes. When there are few censored funds, using these variables to account for time heterogeneity is feasible (Lawless, 2003). Unfortunately, our narrow time window and the large number of censored funds precludes their use.

The Cox PH under competing risks makes additional assumptions that need clarification, in addition to that regarding time homogeneity. First, the proportional hazards assumption stipulates predictor variables to have a multiplicative effect on the hazard function, so that the hazard function for two funds with different characteristics differs only by a constant. Second, it requires independent censoring. This implies that hedge funds are not voluntarily dropping out of the HFR database because they are facing impending liquidation and want to avoid the bad publicity brought on by a recorded liquidation. Third, it assumes that the criteria for entry into HFR is consistent. Fund managers start reporting to HFR usually after the fund has been in operation for 1 or 2 years. If the market demand for hedge funds rises, managers may want to start reporting immediately after fund creation. Those funds would experience longer lifetimes simply because they started reporting earlier.

To assess the predictive power of the competing risks model, we run the model in Table 2.2 using in-sample data running from 1994 to 2002. For each fund we obtain a predicted hazard using coefficients for liquidation under competing risks, and another predicted hazard using coefficients under all exits. We select a cut-off point for the hazard, and compare the number of out-of-sample funds that actually liquidate in 2003 with predicted hazard above the cutoff. We then vary the cut-off and obtain the two plots in Figure 2.2. For cut-offs below 1, the two predicted hazards perform similarly. For larger cut-offs, however, the liquidation coefficients are better at predicting out-of-sample liquidation. For example, when the cut-off is 2, roughly 40% of out-of-sample funds with predicted liquidation hazard above the cut-off actually liquidate, but less than 10% of those with predicted all exits hazard above the cut-off actually liquidate. This implies that a hazard predicted in-sample and based on liquidation alone is more likely to identify funds that liquidate out-of-sample, than a predicted hazard that uses all exits.

2.4.3 Cross-Sectional Determinants of Liquidation

Several studies analyze cross-sectional determinants of survival with a probit or logit model, with dependent variable defined as a binary variable corresponding to whether a fund is alive or defunct. If longitudinal models of survival are hampered by the aggregation of exit types, however, then cross-sectional models ought to suffer the same fate. Baquero, ter Horst, and Verbeek (2005) run a probit model on fund liquidation. This approach assumes that all non-liquidated funds exiting the database are in fact alive. We refine their approach, by applying a multinomial logit regression model with four possible outcomes: alive, liquidated, closed to new investment, or no longer reporting. The live funds are defined as the baseline category, so that for any given exit the coefficients represent the change in probability (on the logit scale) of that exit (Agresti, 2002). For comparative purposes we also run a logistic regression model that combines all exits. The multinomial model does not produce estimates of survival time. Rather, it produces estimated probabilities of each exit, based on given values of predictor variables. We use a multinomial model for nominal response categories, rather than a multinomial model for ordinal responses, since the exit types cannot be ranked.

The results of the multinomial and logistic models are presented in Table 2.3. Funds with high returns, low returns volatility, a large asset base, low asset volatility, and a hurdle rate tend to remain alive longer. This is consistent with the results of the Cox PH model presented in Table 2.2 and those encountered in the literature. Our coefficient of $\beta = -0.2845$ for returns under all exits is close to the value of -0.2440 obtained by Baba and Goko (2006). As in Brown, Goetzmann, and Park (2001) we also find that older funds are at decreased risk of exit, which reflects their argument that seasoned managers of well-established funds benefit from a long experience, and are likely to survive longer. Our multinomial model indicates that the protective effects of predictor variables is stronger for liquidation than for the other exits.

2.4.4 Estimates of Survivorship Bias

The widely-varying estimates of survivorship bias encountered in the literature could partly be due to the heterogeneity of the defunct pool of funds, and to the finding of Fung and Hsieh (2002) and Liang (2000) that some defunct funds have very good returns and are alive and well. Panel A of Table 2.4 indicates that varying the composition of the defunct pool can substantially change estimates of survivorship bias. Including all defunct funds leads to a yearly survivorship bias of 1.51%, consistent with the estimates of Liang (2001), Edwards and Caglayan (2001), and Amin and Kat (2003). When funds no longer reporting are excluded from the defunct group, the estimate jumps to 3.26%, similar to that obtained by Brown, Goetzmann, and Ibbotson (1999) and Fung and Hsieh (2000). When liquidated funds are excluded, it drops to -0.37%, which reflects the argument of Liang (2001) that poor performance is the main reason for liquidation. When liquidated funds only constitute the defunct group, the estimate increases to 4.51%. Baquero, ter Horst, and Verbeek (2005) refer to this as "liquidation bias", and estimate it at 1.52% yearly. Our annual estimate of 4.51% is higher, and slightly higher than most other estimates found in the literature.

2.4.5 Hedge Fund Attrition Rates

Getmansky, Lo, and Mei (2004) and Amin and Kat (2003) find an increase in hedge fund attrition over the 1994 to 2003 period. In those studies, however, liquidation was not isolated from the other exits. We estimate the attrition rate of funds due to liquidation only, due to other exits, and due to all exits combined.

Table 2.5 shows that the attrition rate of funds closing to new investment increased from 0.2% in 1994, to 1.6% in 2003. This supports the argument of Amin and Kat (2003) that fund managers are closing down faster nowadays than one decade ago. The increase in attrition can therefore be partially attributed to the increase in funds no longer reporting. When liquidation only is considered, attrition is estimated at 3 to 5% annually, with no apparent increase. These estimates are higher than those obtained by Baquero, ter Horst, and Verbeek (2005), but they are very close to those of Baba and Goko (2006). The results of this analysis suggest that attrition may not be increasing as dramatically as previously thought. Indeed, we find that attrition rates based on liquidation only are roughly one-half as large as those based on all exits combined. When exits are combined, the attrition rates are close to those obtained by Getmansky, Lo, and Mei (2004) and Baquero, ter Horst, and Verbeek (2005).

2.4.6 Hedge Fund Survival Time

In this section we adopt the view of a prospective long-term investor who wishes to commit money to a hedge fund. We use the Kaplan-Meier estimator to produce two estimates for the survival function, one for which a fund's lifetime is the time until liquidation, and the other as the time to any exit.

Figure 2.3 presents the estimates of survival function for time until liquidation (upper lines) and for time until any exit (lower lines). The solid lines are generated using HFR data, and the dashed lines with TASS data. With the HFR data, the mean survival time until liquidation is 8.3 years, while the mean survival time until any exit is 6.5 years. Isolating liquidation leads to a upward revision of almost two years. Of course, some funds exit HFR because they are at risk of liquidation, which violates the assumption of independent censoring. Unfortunately, those funds cannot be identified in the database. Notwithstanding this violation, the reason for the upward correction is mathematical, because the Kaplan-Meier estimator treats non-liquidated exited funds as censored at the time of exit, rather than as failed. The economic implication is that the mean survival time based on all exits is biased downwards. Investors can therefore expect longer survival than that suggested by the aggregated-exit model.

An investor may wish to estimate the expected survival time of a hedge fund, based on its characteristics and performance. The Cox PH model cannot be used for this, since it does not produce actual estimates of survival time, only of hazard ratios. We use the accelerated failure time (AFT) Weibull regression model, which specifies $\log(T) = \alpha + Z^T\beta + \sigma W$ for the log-survival time, where Z and β denote vectors of predictor variables and regression coefficients, respectively, σ denotes a scale parameter, and W follows the extreme value distribution (but T follows the Weibull distribution). Since the expected value of W is not zero, the expected value of the log survival time $Y = \log(T)$ of a hedge fund with predictor variable values $Z = Z_0$ is not $\alpha + Z_0^T\beta$. It is possible, however, to obtain an estimate of the median log-survival time, $Y_{50} = \alpha + Z_0^T\beta + \sigma W_{50}$, where $W_{50} = \log(\log 2)$ is the 50th percentile of the extreme value distribution. Exponentiation of Y_{50} produces an estimate of the median survival time (Kalbfleisch and Prentice, 2002).

Table 2.6 presents estimates of the AFT model under competing risks. In this model a positive (negative) coefficient leads to an increase (decrease) in survival time. Unfortunately, it is not possible to compare numerically the effects of the predictor variables from the Weibull model to those from the Cox PH model, since the Weibull model produces estimates that act directly on the survival time, while the Cox PH model produces estimates that act on the hazard function. However, it is possible to compare the relative magnitude of predictor variable effects within each model, and whether these effects act positively or negatively effect on hedge fund longevity. In this sense, the results of the AFT model are consistent with those of the Cox model. Hence, the effects of returns and assets under management are strongest for liquidation. High returns and a large asset base, and low volatility in returns and assets, increase survival time. The presence of a hurdle rate is also positively related to survival, while high incentive fees are negatively related. We find high management fees to decrease the time until a fund closes to new investors, but as in Table 2.2 we find no effect of minimum investment on any of the exits. The results of Table 2.6 support the idea that the factors driving liquidation are different from those driving the other exits. It also highlights the need to isolate liquidation from the other exit types if those factors are to be accurately identified and measured.

Our AFT model assumes that the survival times follow a Weibull distribution. While a wide range of distributions can be used for the random disturbance W, the Weibull distribution is flexible enough for most applications (Kalbfleisch and Prentice, 2002). When $\sigma = 1$ in the Weibull model, the distribution for W reduces to an exponential. All estimates of σ in Table 2.6 are statistically different from 1 at the 5 percent level, which implies that $\sigma \neq 1$ so the Weibull distribution is better suited at describing survival times than the exponential (test results not shown). The fit of the AFT can be assessed with a probability plot, which should resemble a straight line if the AFT model is well specified. For each of the models in Table 2.6, the probability plots all resemble approximately a straight line (plots not shown).

Based on the estimates of the AFT model in Table 2.6, we can estimate the average time that a hedge fund with certain characteristics can be expected to survive, and how changing these characteristics can increase the expected lifetime. Table 2.7 presents the median survival time, $T_{50} = \exp(Y_{50})$, of four hypothetical hedge funds. In these calculations only variables that are significant at the 5 percent level or better are retained. Fund 1 has a an average return and volatility of one percent each over the last twelve months of observation, no highwater mark or hurdle rate, incentive and management fees of 20 percent and 2 percent respectively, a minimum investment of \$250K and mean and volatility of assets under management (AUM) over the last twelve months of observation of \$100M each. Panel A of Table 2.7 indicates that an investor can expect such a fund to survive 2.8 years before exit from the database, but 5.8 years before liquidation. Fund 2, which is identical to Fund 1 except that its mean AUM is \$200M, can be expected to survive 6.9 years before liquidation. The results of two other hypothetical funds are also presented. In all four cases, the time to liquidation is roughly twice as long as the time to all exits. This suggests that estimates of hedge fund lifetimes based on models that aggregate exits are misleading, since investors can except lifetimes roughly twice as long as those suggested by aggregated models.

2.4.7 Robustness Checks

To ensure that our results are not hampered by our choice data (HFR), we perform the analyses on 2,813 live and 1,821 defunct funds from the TASS database over the same time period. We define three groups of defunct funds in TASS, to match the three groups from HFR: (1) liquidated (927 funds), (2) no longer reporting (523 funds) (3) others (371 funds, including funds unable to contact (157), unknown (134), merged fund (64), closed (7), missing (6), and dormant (3)). Figure 2.3 indicates that the estimates for survival time until liquidation (upper lines) and for survival time until any exit (lower lines) are approximately the same with HFR and TASS. Despite the small overlap of common funds across both databases (Liang, 2000), the survival experience of both cohorts of funds is strikingly similar. The graphs from the TASS data are smoother, especially at the tails, which reflects the greater number of defunct funds in that database.

The results of the robustness checks on the multivariate models and the attrition rates appear in Table 2.8, in Panel B of Tables 2.4 and 2.7, and in Table 2.5. Table 2.5 indicates that the attrition rates due to liquidation (first set of columns) and for all exits (last set of columns) are similar under HFR and TASS. The survivorship bias, however, is higher under TASS (Table 2.4). Unfortunately, we do not have access to the hurdle rate in TASS. In general, the results from the TASS data in Table 2.8 are comparable to those from the HFR data in Tables 2.2, 2.3, and 2.6, with one notable exception regarding the highwater mark. The TASS data indicate that a highwater mark is associated with a decreased risk of liquidation, the opposite of what was found with HFR. There are possible explanations for each effect. The HFR data suggests that managers under their highwater mark have the incentive to voluntarily liquidate their funds. Hence, a highwater mark hastens liquidation. The TASS data, however, could reflect the fact that skilled managers have the confidence to impose a highwater mark on their performance. In this case, a highwater mark indicates high manager skill and a decreased risk of liquidation. Exactly which effect is dominant is difficult to ascertain. The

TASS data, however, produce a hazard ratio of $HR = 0.464$ for the highwater mark, which is close to the estimate of 0.584 obtained by Baba and Goko (2006). Similarly, the estimate of $\beta = -0.283$ for age in the logit model is comparable to $\beta = -0.36$ obtained[1] by Chan et al. (2005). Finally, Table 2.8 indicates that the $HR = 0.745$ for returns is substantially lower than $HR = 0.904$ using HFR (Table 2.2). Hence, the protective effect of high returns on liquidation is much more evident with the TASS data. These differences could be due to differences in database composition, since defunct funds are under-represented in HFR relative to TASS. Indeed, Panel B of Table 1 indicates that roughly 25% of usable funds in HFR are defunct. In the TASS database, however, 39% of usable funds are defunct.

2.5 Discussion

The results of this chapter raise several issues that merit discussion. A low survivorship bias implies that investors need not be concerned with portfolio performance when hedge funds exit the database. This sense of security is justified when funds exit for reasons other than imminent liquidation. When funds liquidate, however, investors will experience very poor performance. Survivorship bias and survival are therefore linked: since most of the bias results from liquidated funds, it is important for investors to avoid investing in funds that are likely to liquidate.

Hedge funds may perform poorly during bad economic times, such as during periods of slow economic growth or during recessions. Smaller funds may have an insufficient asset base to withstand hard times for an extended period, which could lead to their liquidation when economic conditions deteriorate. Hence, lagged economic indicators may prove to be useful predictors of liquidation.

[1] Chan et al. (2005) obtain $\beta = -0.03$ for age measured in months, so the estimate for age in years is $\beta = -0.03 \times 12$.

We exclude funds born before 1994, which can produce underestimates of survival because long-lived funds born before 1994 are not included. This bias is mitigated by short-lived funds that were born and died before 1994, since those funds are not included in HFR. By analyzing funds born after 1994 only, we exclude both long- and short-lived funds from the sample, but it is impossible to ascertain what potential impact such an exclusion has on our estimates. Barès, Gibson, and Gyger (2001) do not exclude funds born prior to 1994 and find a fifty percent survival time of over ten years. It is therefore possible that hedge funds live much longer than some studies, including this study, suggest.

We have not assessed the impact of capital flows on liquidation. Funds experiencing large outflows may find it difficult to meet their overhead costs. This would be even more dramatic for funds that have poor returns and fall under their highwater mark. Capital flow, modeled as a time dependent variable, might therefore be a strong predictor of liquidation. Flows are partly reflected by assets, however, so the effect of flows can likely be captured by assets. In a logit model, Chan et al. (2005) find flows to be a stronger predictor than assets, but most of their effect was attributed to the last twelve months prior to exit from the database and that study did not separate liquidation from the other exit types. Funds that exit because they are closed to new investment may experience lower capital flows simply because they are refusing new investors. Moreover, including both capital flows and assets creates an endogeneity problem, since assets are not only determined by returns, but also by capital flows.

Our choice of a 12-month window for modeling monthly returns and AUM as time dependent variables is arbitrary. However, different window sizes (6, 18, and 24 months) produced very similar results in the competing risks model. We are therefore confident that the effects of returns and AUM is not dependent on the window size, and that our choice of a 12-month window is not driven by a need to produce significant effects.

We have assumed that liquidation is always an undesirable outcome. Yet some hedge funds liquidate simply because their managers have earned a lot of money, and wish to cease operations. In that case, investors redeem their money and do not suffer losses. Most liquidations, however, are associated with large capital losses, such as the liquidations of LTCM and Amaranth. The findings presented in Table 2.1 and illustrated in Figure 2.1 suggest that liquidated funds lose money, and that liquidation is usually an undesirable outcome for hedge fund investors.

2.6 Conclusion

The amount of capital being allocated to hedge funds is growing at an exponential rate and the industry is attracting heavyweight investors such as the California Public Employees' Retirement System (CalPERS), and the Harvard University endowment fund. Institutions have expressed a desire to invest into hedge funds on a long-term basis, and as such, are on the lookout for funds likely to survive a long time and avoid liquidation. Survival analysis can help these investors identify funds with longevity. In order for this to be done properly, however, liquidation must be isolated from the other exits hedge funds can experience.

The main appeal of alternative investments such as hedge funds and Commodity Trading Advisors (CTA), a special class of hedge fund that invests in futures contracts, is their ability to generate positive returns regardless of market conditions. Hence, hedge funds and CTAs should be active asset managers, and not passive asset gatherers. In the next chapter we attempt to determine why some CTAs behave like indexers. In particular, we show how the double fee structure charged by CTAs can change the incentives of their managers as they grow in size and attract more risk averse clients, such as pension funds.

Table 2.1 Descriptive Statistics of Live and defunct Funds

PANEL A: Number of live funds and exited funds for each exit type, with the mean and standard deviation of their returns. PANEL B: Number of live funds and exited funds for each exit type, with the mean and standard deviation of the assets under management. Returns and assets are calculated over their entire history (first set of columns), over the last twelve months before exit (second set), and over the last six months before exit (third set). Only funds born on or after January 1994 are used.

Panel A: Returns (%)		Entire History		Last 12 mo		Last 6 mo.	
	# Funds	Mean	Std Dev	Mean	SD	Mean	SD
Live	2,625	1.09	4.97	1.34	3.56	1.32	3.23
Defunct	1,428	0.95	7.12	0.39	8.15	0.33	8.62
No Reporting	621	1.26	7.07	0.82	8.41	0.68	9.23
Liquidated	585	0.70	7.33	−0.04	8.12	−0.09	8.36
Closed	222	0.78	6.78	0.34	7.41	0.48	7.37
Panel B: Assets ($M)		Entire History		Last 12 mo		Last 6 mo	
	# Funds	Mean	Std Dev	Mean	SD	Mean	SD
Live	1,991	101	330	127	339	138	357
Defunct	647	37	82	40	95	41	105
No Reporting	261	53	118	59	129	61	139
Liquidated	275	27	49	25	60	25	71
Closed	111	30	58	35	66	35	66

Table 2.2 Hazard Ratios from the Cox Proportional Hazards Model

Hazard ratios for the competing risks Cox proportional hazards (PH) model estimated for each exit, and for the conventional Cox PH model for all exits combined, using HFR data. The columns for Liquidated (2st column), No Longer Reporting (3rd column) and Closed to New Investment (4th column) treated simultaneously is the competing risks model. The model for All Exits combined (5th column) is the conventional Cox PH model. Avg_Ret(t) and StdDev_Ret(t) are time dependent predictor variables for the mean and standard deviation of returns over one year, respectively, each expressed as a monthly percentage. Highwater and Hurdle are fixed binary predictor variables taking on the value one if the fund has a highwater mark and a hurdle rate, respectively. IncFee and ManFee are fixed predictor variables for incentive fee and management fee respectively, each expressed as a percentage. MinInv is a fixed predictor variable for minimum investment, expressed in $M. Avg_AUM(t) and StdDev_AUM(t) are time dependent predictor variables for the mean and standard deviation of assets under management over one year, respectively, expressed in $100M. Hazard ratios significant at the 1 and 5 percent level are denoted ** and * respectively.

Variable	Liquidated	No Reporting	Closed	All Exits
Avg_Ret(t)	0.904**	0.959**	0.918**	0.931**
StdDev_Ret(t)	1.031**	1.013*	0.964**	1.022**
Highwater	1.716**	1.030	1.062	1.238*
Hurdle	0.253**	0.248**	0.165**	0.236**
IncFee	1.013*	1.019*	1.022	1.016**
ManFee	0.863	0.857*	0.976	0.881**
MinInv	0.939	0.946	1.035	0.977
Avg_AUM(t)	0.634**	0.994	0.587*	0.910**
StdDev_AUM(t)	1.243**	1.019	1.085	1.058**

Table 2.3 Logistic Regression and Multinomial Regression of Hedge Funds

Estimated regression coefficients from the logistic model (grouping all exit types together) and from the multinomial logit model (keeping exits separate), using HFR data. Mean Ret and StdDev Ret are mean and standard deviation of returns expressed as a percent, respectively, during the last 12 months of observation, Highwater and Hurdle are each binary variables for the presence of a highwater mark and a hurdle rate, respectively, Incentive Fee and Management Fee are each expressed as a percent, and Minimum Investment is expressed in $100K. Mean AUM and StdDev AUM are mean and standard deviation of assets under management expressed in $M, respectively, during the last 12 months of observation. Age is the age of the fund, in years. Coefficients significant at the 1 and 5 percent level are denoted ** and * respectively.

	Logistic	Multinomial Logit		
Variable	All Failures	Liquidated	No Reporting	Closed
Intercept	1.2631**	0.4556	0.4749	−0.8587*
Mean Ret	−0.2845**	−0.3288**	−0.2555**	−0.3067**
StdDev Ret	0.3312**	0.3447**	0.3228**	0.2853**
Highwater	−0.1088	0.0312	−0.1873	−0.1961
Hurdle	−2.0500**	−2.0266**	−2.0189**	−2.1757**
Incentive Fee	0.0222	0.0184	0.0258	0.0258
Management Fee	−0.2808	−0.3352	−0.3160	−0.0814
Minimum Investment	0.0148*	0.0128	0.0135*	0.0208**
Mean AUM	−0.0006*	−0.0017**	−0.0004	−0.0010
StdDev AUM	0.0014*	0.0020**	0.0011	0.0009
Age	−0.1875**	−0.1971**	−0.1863**	−0.1440**

Table 2.4 Estimates of Survivorship Bias

Estimates of monthly and yearly survivorship bias obtained by defining live funds as those alive at December 2003, and defunct funds as No Longer Reporting, Liquidated, or Closed to New Investment (or Others for TASS data). Bias/Mo is the monthly difference between Live Returns and Defunct Returns. Bias/Yr is Bias/Mo multiplied by twelve. All entries are percentages. PANEL A: HFR data. PANEL B: TASS Data.

PANEL A: HFR Data Defunct Group	Live Return	Defunct Return	Bias/Mo	Bias/Yr
No Reporting + Liquidated + Closed	1.043	0.917	0.126	1.51
Liquidated + Closed	1.043	0.771	0.272	3.26
No Reporting + Liquidated	1.043	0.900	0.143	1.72
No Reporting + Closed	1.043	1.074	−0.031	−0.37
Liquidated	1.043	0.667	0.376	4.51
Closed	1.043	0.999	0.044	0.53
No Reporting	1.043	1.103	−0.060	−0.72
PANEL B: TASS Data Defunct Group	**Live Return**	**Defunct Return**	**Bias/Mo**	**Bias/Yr**
No Reporting + Liquidated + Others	1.000	0.653	0.347	4.16
Liquidated + Others	1.000	0.542	0.458	5.50
No Reporting + Liquidated	1.000	0.627	0.373	4.48
No Reporting + Others	1.000	0.907	0.093	1.12
Liquidated	1.000	0.455	0.545	6.54
Others	1.000	0.744	0.256	3.07
No Reporting	1.000	0.887	0.113	1.36

Table 2.5 Annual Attrition Rates

Annual attrition rates from HFR and TASS, calculated as the proportion of hedge funds experiencing each type of exit (Liquidation, Closed to New Investment, No Longer Reporting (or Others for TASS data), and experiencing any type of exit (All Exits). All rates are expressed as a percentage.

	Liquidated		No Reporting		Closed/Others		All Exits	
Year	HFR	TASS	HFR	TASS	HFR	TASS	HFR	TASS
1994	1.1	2.1	0.8	0.6	0.2	1.1	2.1	3.7
1995	2.3	4.2	2.0	0.9	0.1	1.8	4.4	6.9
1996	5.6	5.1	4.3	1.3	0.4	4.2	10.3	10.7
1997	4.4	4.9	4.9	1.2	1.0	1.4	10.2	7.5
1998	5.0	6.7	9.8	1.4	1.6	1.8	16.4	10.2
1999	3.8	5.5	4.7	2.3	1.6	2.5	10.1	10.3
2000	4.6	4.5	8.2	3.6	1.4	3.4	14.2	11.5
2001	3.7	4.6	4.9	5.4	2.0	1.8	10.7	11.7
2002	4.3	5.3	3.7	3.5	1.7	1.5	9.7	10.4
2003	4.2	4.8	3.6	2.9	1.6	0.8	9.3	8.5

Table 2.6 Accelerated Failure Time Regression Model

Estimated regression coefficients from the AFT Weibull survival model, using HFR data. Mean Ret and StdDev Ret are mean and standard deviation of returns expressed as a percent, respectively, during the last 12 months of observation, Highwater and Hurdle are each binary variables for the presence of a highwater mark and a hurdle rate, respectively, Incentive Fee and Management Fee are each expressed as a percent, Minimum Investment is expressed in \$100K, Mean AUM and StdDev AUM are mean and standard deviation of assets under management expressed in \$M, respectively, during the last 12 months of observation. Coefficients significant at the 1 and 5 percent level are denoted ** and * respectively.

	Estimated Regression Coefficient			
Variable	Liquidated	No Reporting	Closed	All Exits
Intercept	2.1127**	1.9135**	2.4588**	1.5143**
Mean Ret	0.0292**	−0.0038	0.0231	0.0119*
StdDev Ret	−0.0082**	0.0026	0.0328**	−0.0033*
Highwater	−0.2207*	0.0228	0.1497	−0.0476
Hurdle	0.8601**	0.9248**	1.1502**	0.9235**
Incentive Fee	−0.0103*	−0.0139**	−0.0202**	−0.0131**
Management Fee	−0.0413	0.0282	−0.1304*	−0.0340
Minimum Investment	0.0014	0.0021	−0.0013	0.0006
Mean AUM	0.0016**	0.0001	0.0007	0.0006**
StdDev AUM	−0.0011**	−0.0003	−0.0001	−0.0006**
Scale Parameter (σ)	0.5819	0.5996	0.5900	0.5925

Table 2.7 Estimates of Median Survival Time

Estimates of median survival time, $T_{50}=\exp(Y_{50})$, for hedge funds, in years. Only variables significant at the 5% level or better in Table 2.6 have been retained. Fund 1 has mean and standard deviation of returns over the last 12 months of observation of 1% each, no highwater mark or hurdle rate, incentive and management fees of 20% and 2% respectively, minimum investment of $250K, and mean and standard deviation of assets under management (AUM) over the last 12 months of observation of $100M each. Fund 2 is identical to Fund 1, except that its mean AUM is $200M. Fund 3 is identical to Fund 2 except that its monthly standard deviation of return is 2%. Fund 4 is identical to Fund 3, except that its incentive fee is reduced to 15%. PANEL A: HFR Data. PANEL B: TASS Data.

PANEL A: HFR Data	All Exits	No Reporting	Liquidated	Closed
T_{50} for Fund 1	2.8	4.1	5.8	5.8
T_{50} for Fund 2	3.0	4.1	6.9	5.0
T_{50} for Fund 3	3.1	4.1	7.1	5.0
T_{50} for Fund 4	3.3	4.4	7.4	5.5
PANEL B: TASS Data	All Exits	No Reporting	Liquidated	Others
T_{50} for Fund 1	7.1	16.3	7.2	4.0
T_{50} for Fund 2	10.2	16.3	13.7	6.9
T_{50} for Fund 3	11.0	17.1	15.3	6.9
T_{50} for Fund 4	11.9	17.1	17.4	11.9

Table 2.8 Robustness Checks

Estimated coefficients for liquidation (Liquid) and for all exits (All) from the Cox Proportional Hazards (PH) model, Multinomial model, and Accelerated Failure Time (AFT) Weibull survival model, using TASS data. Mean Ret and StdDev Ret are mean and standard deviation of returns expressed as a percent, respectively. Highwater and Hurdle are each binary variables for the presence of a highwater mark and a hurdle rate, respectively, Incentive Fee and Management Fee are each expressed as a percent, Minimum Investment is expressed in \$100K, Mean AUM and StdDev AUM are mean and standard deviation of assets under management expressed in \$M, Age is in years. Entries for the Cox PH model are hazard ratios, other entries are beta coefficients. Mean Ret, StdDev Ret, Mean AUM, and StdDev AUM are obtained during the last 12 months of observation for the Multinomial and AFT models, and are treated as time-dependent variables in the Cox PH model. Coefficients significant at the 1 and 5 percent level are denoted ** and * respectively.

	Cox PH		Multinomial		Weibull AFT	
Variable	Liquid	All	Liquid	All	Liquid	All
Intercept	–	–	−1.138**	−0.345*	2.638**	2.137**
Mean Ret	0.745**	0.816**	−0.552**	−0.500**	0.109**	0.072**
StdDev Ret	0.950**	1.016*	0.218**	0.265**	0.003	−0.025**
Highwater	0.438**	0.464**	−1.064**	−1.004**	0.513**	0.458**
IncFee	1.046**	1.030**	0.057**	0.041**	−0.026**	−0.016**
ManFee	1.078	0.985	−0.233**	−0.337**	−0.021	0.030
MinInv	0.951	0.996	0.001*	0.000	−0.001**	−0.001*
Mean AUM	0.358**	0.814**	−0.004**	−0.001*	0.006**	0.004**
StdDev AUM	1.179	0.434*	0.004**	0.002	−0.006**	−0.003
Age	–	–	−0.306**	−0.283**	–	–
Scale (σ)	–	–	–	–	0.706	0.691

Figure 2.1 Capital Growth and Erosion

Mean monthly net asset value of hedge funds during the last forty-eight months of observation, in \$M. Live funds are denoted with $\circ$, funds no longer reporting with $\boxdot$, funds closed to investment with $\times$, and liquidated funds with a solid line.

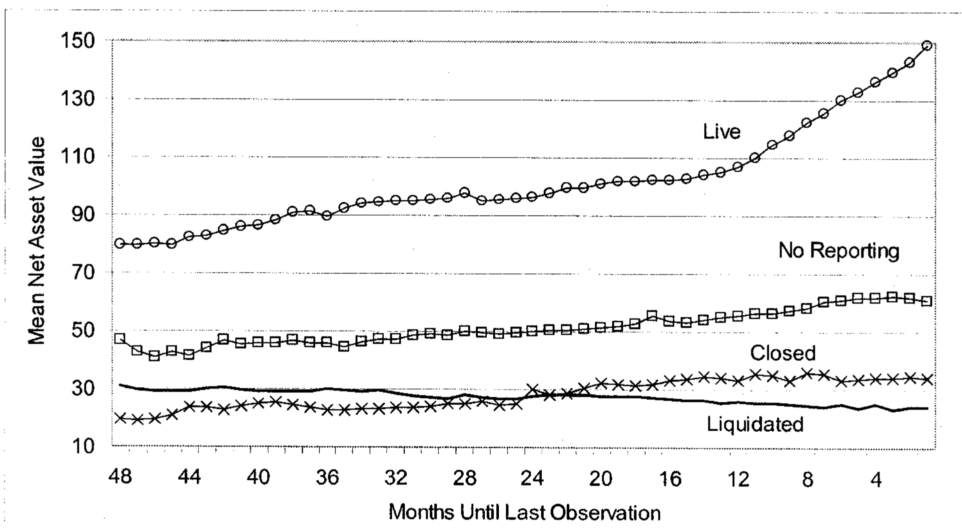


Figure 2.2 Out-of-Sample Predicted Liquidation from Cox PH Model

Percentage of out-of-sample funds experiencing liquidation, when the in-sample hazard is estimated using the liquidation hazard from the competing risks Cox proportional hazards model, and when the in-sample hazard is estimated using the all exits hazard from the single-outcome Cox proportional hazards model. For each fund, the in-sample liquidation hazard is estimated based on the fund's predictor variables. For each cut-off (x-axis), the percentage of out-of-sample funds with estimated liquidation hazard above the cut-off that actually liquidate is obtained, which produces the solid line identified with triangles. This is repeated with the in-sample all exits hazard on each fund, which produces the solid line identified with squares. The dashed lines are 95 percent confidence bands. The in-sample period runs from 1994 to 2002 and the out-of-sample period consists of funds experiencing liquidation in 2003.

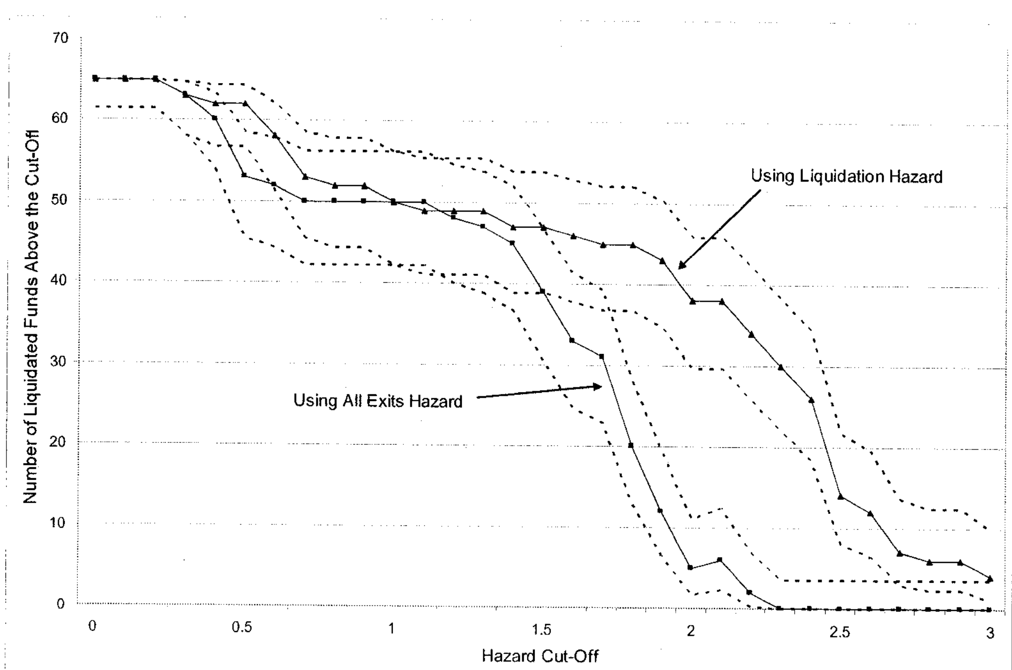
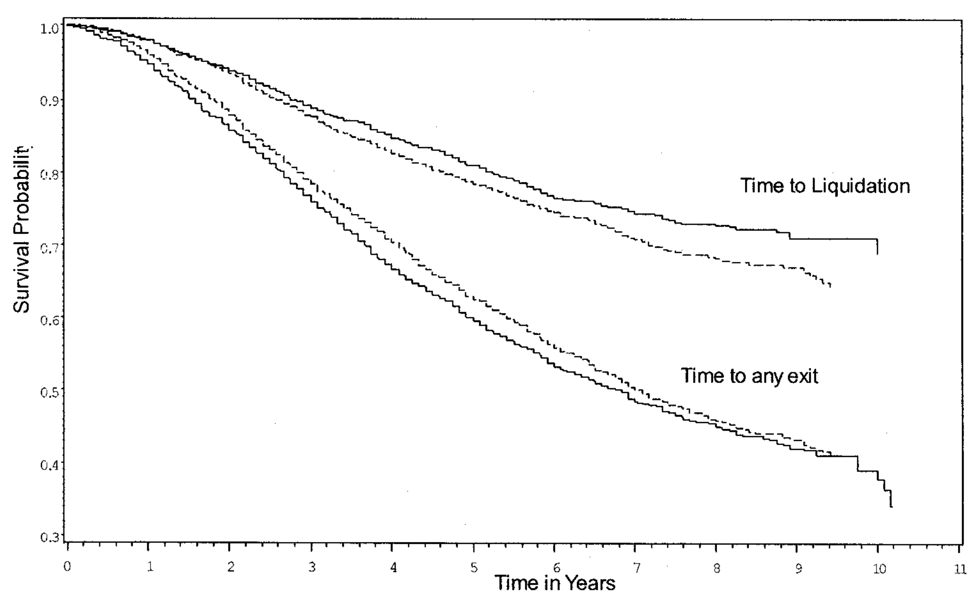


Figure 2.3 Kaplan-Meier Estimator of Survivor Function

Kaplan-Meier estimates of the survival function $\widehat{S}(t)$. The upper lines are the estimates of survival time until liquidation, and the lower lines are estimates of survival time until any exit. The estimates of $\widehat{S}(t)$ using HFR data are represented by solid lines, and those using TASS are represented by dashed lines. The horizontal axis is survival time in years, t, and the vertical axis is the survival probability $\widehat{S}(t) = \Pr(T > t)$, where T is a non-negative random variable for the lifetime of a hedge fund.



CHAPTER 3

FEES AND INCENTIVES AMONG CTA MANAGERS

Fabrice Rouah and Susan Christoffersen

3.1 Introduction

Commodity Trading Advisors (CTA) are a special class of hedge fund whose investment strategies revolve around futures contracts. Like most hedge funds, CTAs are remunerated through a two-tier fee system based on both assets under management and performance. The managers of CTAs are therefore tempted in two directions. The first is to post good performance so that the performance-based fee[2] can be earned. As they grow in size, however, this temptation diminishes because they earn an increasing amount of money from their management fee alone. In this chapter we show that small CTAs with high incentive fees and low management fees take on risk and chase high returns, while CTAs with low incentive fees and high management fees have lower risk and diminished returns, and behave like indexers as they grow. In this chapter, we examine fees and incentives among CTAs because CTAs tend to be much smaller than hedge funds. The effect of fees on risk taking might be amplified among managers who administer a small asset base, since those managers would earn very little compensation from their management fee. Hence, the fees/ risk-taking relationship is likely easier to capture among CTAs, who are usually small, but harder to capture among larger hedge funds. The results of this chapter can be extended to hedge funds, since hedge funds also charge a dual fee structure that is directly observable. Since the effects of incentives on size we document in this chapter might be mitigated in very large funds, however, our results are likely applicable to small hedge funds only.

[2] In this chapter, we refer to the performance-based fee as the *incentive* fee.

Money managers are often characterized by an inverse size-performance relationship. There are three competing theories to explain this phenomenon in mutual fund managers. The first is liquidity constraints, since larger funds cannot move in and out of positions as fast as they might like. Hence, they are less optimal in their trading strategies than smaller funds, which are not hampered by liquidity constraints. The second is that large, older funds have a flow/performance relationship which is not very convex. Small, young funds have a strong convex relationship, so they are rewarded with capital inflows when they perform well. Large, older funds, however are not well rewarded, so their incentive to post good returns is decreased. The third theory is due to manager reputation and career concerns. Fund managers that amass a large asset base become concerned with capital preservation and their reputation. In doing so, they become more risk averse and their performance decreases.

In this chapter we show that the dual fee structure charged by CTAs can serve as an additional theory for this relationship. The third theory can be tested by examining the returns and volatility of CTAs for which the risk incentives are high and comparing them to the returns and volatility funds of CTAs for which the risk incentives are low. If managers become increasingly risk averse as their asset base grows, we would expect the relationship between size and returns (and between size and volatility) to be more negative for CTAs for which the risk incentives are highest. This is exactly one of the findings of this chapter.

3.2 Literature Review

While most mutual fund managers do not charge incentive fees, Christoffersen (2001) finds that poorly performing managers of institutional funds sometimes waive their fees to bolster modest returns and attract investors. This implies a positive, indirect relationship between fees and performance.

Both Golec (1993) and Diz (2004) find a positive relation between incentive fees and performance in the CTA industry. Golec (1993) finds a large incentive fee to be associated with good performance and high risk-taking. Diz (2004) finds the positive relation between the incentive fee and performance to persist even when adjusted for CTA characteristics. The effect of management fee on returns, however is much weaker. Golec (2005) finds a large asset base to be negatively related to returns, but Diz (2004) and Gregoriou (2006) each find a positive, albeit weak, relation. There is also evidence that incentive and performance fees are related to volatility. Diz (2004) finds a positive and significant effect of both fees on volatility, but the coefficients for Golec's (1993) regression fail to achieve significance. This could be partly explained by the smaller sample used in the latter study (80 CTAs versus 1,253 in Diz's study).

Golec (1993) argues that older CTAs may have acquired a good reputation and amassed a large asset base. The threat of outflows from negative returns, coupled with the desire to preserve their reputation, makes them more risk averse than young[3] CTAs. Reputation effects among mutual fund managers manifest themselves in several forms and are also dependent on the age of the managers. Chevalier and Ellison (1999) report that young managers are more likely to become terminated following poor performance. Reputation also affects inflows and outflows of money to and from mutual funds. Chevalier and Ellison (1997), Sirri and Tufano (1998), and Del Guercio and Tkac (2002) find a convex relationship between performance and flows. Well-performing funds are rewarded with increased asset inflows, but poorly-performing funds are not penalized with increased outflows. Chevalier and Ellison (1997) find

[3] In this chapter, "young" and "old" CTAs refer to the age of the CTA, in terms of how long the CTA has been managing money. It does not refer to the age of the managers or directors of the CTA.

a flat performance/flow relationship for older, well-established funds only, and a convex relationship for young funds. Hence, good performance attracts investors to young funds, but not necessarily to older funds. Agarwal, Daniel, and Naik (2004) find a convex relationship between flows and performance among hedge funds, but Ding et al. (2007) show that this relationship is only present in hedge funds without share restrictions.

Risk-taking by mutual funds also depends on manager age and size. Chevalier and Ellison (1997) find that young managers with poor performance in a given year and faced with the possibility of increased outflows the following year, have an incentive to increase risk to bolster returns. Older funds are not faced with increased outflows and will not increase risk. Among hedge funds and CTAs, reputation plays a similar role. Young CTAs are more likely to take on more risk and adopt more aggressive strategies, in order to bolster returns (Howell, 2001). This, in turn, helps to develop a reputation and attract clients. As the CTA grows, it attracts more conservative and risk-averse clients, such as pension funds, and its manager will come to under pressure to adopt more conservative strategies and reduce risk-taking. Golec (1993) points out that large CTAs can suffer from diseconomies of returns, since a large asset base makes it harder to trade positions without attracting attention from other market participants. A large asset base may also force CTAs to hold more diversified portfolios than they desire, because of limits on the number of futures contracts available for trading.

In this chapter we examine the effect of fees from a different perspective. As a CTA grows, its managers earn more and more of their compensation from the management fee, and less from the incentive fee. If the CTA holds enough assets, and if the management fee is large, the compensation from the management fee alone may be sufficient to pay its expenses and dole out sizeable bonuses to its managing partners. It stands to reason that such a CTA will be less motivated to earn the incentive fee than a small CTA whose management fee alone cannot guarantee that its overhead costs are met. Hence, our hypothesis is that once a CTA reaches a certain size, it may become "fat and happy", reduce risk, become more passive, and behave like an indexer. In other words, it may stop behaving like an asset manager and start behaving like an asset gatherer.

We hypothesize that CTAs with high incentive fees will have the highest incentive to take risk, especially when they hold few assets. This argument can be formulated in terms of overhead costs and market conditions. The management fee alone may not be sufficient for CTAs with few assets under management (AUM) to meet their overhead costs. Those CTAs need to chase high returns to generate profits and incentive fees, even when economic conditions deteriorate. This would be especially true for CTAs with low management fees. Large CTAs, on the other hand, may earn enough compensation from their management fee alone to meet their overhead costs, especially when that management fee is high. When economic conditions are favorable, or during a bull market, those CTAs can chase returns to earn extra compensation. When economic conditions decline, however, they can reduce their risk and rely on the management fee alone to pay their overhead costs until conditions become more favorable.

A simple comparison of these fees across size deciles can shed some light on this issue. CTAs in the first size decile (the smallest CTAs) have average management and incentives fee of 2.11% and 19.6% respectively. CTAs in the last decile (the largest) have average management and incentive fees of 2.

The asymmetric incentive fee may therefore explain the risk-taking behavior of small CTAs, because the asymmetry implies that managers are always rewarded with an incentive fee if the fund generates a profit, but are never penalized beyond capital erosion and investor outflows if the fund loses money. Managers with a small asset base and a large incentive fee have a strong temptation to bolster future returns so that the incentive portion of their compensation can be earned. This can help explain the large decrease in returns and volatility with increasing growth that we document, especially among CTAs with high incentive fees and low management fees.

3.3 Data

We use information on 741 active and 1,683 non-active CTAs from the Barclay Group, Inc. database, covering the period January 1, 1990 to December 31, 2005. For analyses of size and indexing we use the entire period in the database, January 1, 1975 to December 31, 2005. We also use the return on the Standard and Poor's 500 Index (SP500) to proxy equities, the Goldman Sachs Commodity Index (GSCI) for commodities, the Lehmann Brothers Aggregate Bond Index for bonds, returns from the Small Minus Big (SMB), High Minus Low (HML) and Up Minus Down (UMD) portfolios to proxy technical trading, the Stark 300 Trader Index as a CTA benchmark, the price of gold, and the monthly T-Bill rate for the risk-free rate. In analyses of the relationship between size and indexing, we also include the Barclay BTOP CTA Index (BTOP), the Center for International Securities and Derivatives Markets (CISDM) Asset-Weighted CTA Index, and HedgeFund.Net CTA Index. These variables are similar, but not identical, to those used by Liang (2003), Edwards and Liew (1999) and Hübner and Papageorgiou (2004).

Table 3.1 presents descriptive statistics on the sample CTA data. The median monthly return of all CTAs is 0.44 percent. With a monthly standard deviation of 9.20 percent, however, CTAs can be quite volatile. CTAs are generally young and small, with a median assets under management (AUM) of \$4.4M, and aged a median of 4.17 years over the observation period. The distribution of AUM is highly skewed, since the mean AUM is slightly over \$55M. The data reflect the concentration of assets in the CTA industry – a few large CTAs hold the bulk of the assets, while the majority are small. Indeed, of the nearly \$121B held by 741 active CTAs at their last date of reporting, nearly \$96B, or almost 80 percent, was held by 74 CTAs, or ten percent of them (data not shown). The remaining 667 CTAs held an average of slightly over \$38M each.

The smallest return in Table 3.1 is reported as -202%. This can happen if the CTA loses all of its capital and also ends up in debt, as would be the case, for example, when a CTA is faced with large margin calls that cannot be met. Removing the 4 returns with values less than -100% (out of a possible 163,235 monthly returns) had a negligible effect on the value in the first row of Table 3.1.

The median management and incentive fee are 2 and 20 percent, respectively. These numbers are consistent with those of Diz (2003, 2004), who uses the same database, but up to 1998 only. That study found median and mean assets of \$1.8M and \$34.7M, respectively, and the same values for the median management and incentive fees as in Table 3.1. In this paper, however, we wish to differentiate between CTAs with high and low incentive fees. Hence, we define three groups of CTAs, based on the median values of the incentive and management fee. "High" incentive fee CTAs are those with an incentive fee greater than 20 percent, and with a management fee less than 2 percent. "Low" incentive fee CTAs are those with an incentive fee less than 20 percent, and with a management fee of greater than 2 percent. "Others" are all other CTAs. Table 3.1 indicates that most of the CTAs fall in the "Other" category. It also indicates that "High" CTAs tend to be smaller than "Low" CTAs, in terms of median AUM. Hence, CTAs with high management fees may be large enough to earn substantial remuneration from their management fee alone, and may not need to take on risk and chase returns, while the opposite would be true for CTAs with low management fees. In this paper we investigate how the "High" and "Low" CTAs behave as they grow, and argue that the fee differential can serve as an additional driver for the inverse size-performance relationship often observed among money managers.

3.4 Fees and Size, Returns, Volatility

Our hypotheses is that as CTAs grow in size, they become more conservative in their investment strategies and seek to reduce their volatility, but that this reduction in risk comes at the expense of good performance. There are different explanations for the inverse relationship between size and performance among money managers. The first is due to liquidity constraints, because large funds may be forced to hold larger positions than they wish, and may find it difficult to trade without impacting prices (Chen et al., 2003) or suffering diseconomies of returns (Golec, 1993). The second is the convex relationship between flows and fees (Chevalier and Ellison, 1997). Finally, reputation and career concerns may induce managers of large funds to become more risk-averse and reduce their volatility (Brown, Goetzmann, and Park, 2001, Chevalier and Ellison, 1999). In this chapter, we present an alternate explanation. Because of the asymmetric payoff of the incentive fee, managers of large CTAs may derive enough remuneration from their management fee alone to cover their expenses and give them high utility. Smaller CTAs, on the other hand, must earn the additional incentive fee to survive.

In this chapter we hypothesize that CTAs with high incentive fees and low management fees are particularly sensitive to the size/performance relationship. To test this hypothesis, we first divide CTAs into "High", "Low", and

"Others", based on their fees. The "High" group includes CTAs with incentive fee greater than 20% and management fee less than 2%, while the "Low" group, CTAs with incentive fee less than or equal to 20% and management fee greater than or equal to 2%. "Others" are all other CTAs. We then split the assets under management (AUM) of all CTAs into deciles, and compute the mean monthly return and monthly volatility in each group and in each decile. The results appear in Table 3.2 for returns net of all fees, and indicate that the negative relationship between returns and size is particularly strong in the "High" group. Small CTAs in the "High" group have a mean monthly return of 5.19%, while those in the "Low" group, 2.34%. In the largest decile the returns fall to 1.22% and 0.72%, respectively. The negative relationship between volatility and size is also more striking in the "High" group than in the "Low" group. This is consistent with the finding of Golec (1993) that a large incentive fee is linked to high returns and high volatility.

Figure 3.1 illustrates this relationship for both groups by plotting volatility and returns as a function of AUM decile. The "High" group (solid) lines have steep slopes, while the "Low" group (dashed lines) have slope that are much flatter. Hence, the two-tier asymmetric fee structure charged by CTAs can help explain the negative relationship between returns and size. Small CTAs with high incentive fees and low management fees must increase their risk in order to bolster returns and earn enough compensation from the incentive fee. As they grow, this becomes less crucial so their appetite for risk and high returns diminishes. Small CTAs with high management fees and low incentive fees, on the other hand, have less need to generate high returns. Their appetite for risk diminishes also, but not as dramatically.

To formally test the relationship between returns, fees, and size, we run the following model

$$\begin{aligned} y_{it} &= \alpha + \beta_1 High_i + \beta_2 Low_i + \beta_3 \log(AUM_{it}) + \beta_4 High_i \times \log(AUM_{it}) \\ &\quad + \beta_5 Low_i \times \log(AUM_{it}) + \text{control variables} + \varepsilon_{it} \end{aligned}$$

where, for CTA i in year t, $High_i$ is a dummy variable for a CTA in the "High" group, Low_i a dummy variable for a CTA in the "Low" group, $\log(AUM_{it})$ is the logarithm of average yearly AUM, and ε_{it} is an error term. The "High" group consists of CTAs with incentive fee greater than 20% and management fee less than 2%, the "Low" group of CTAs with incentive fee less than 20% and management fee greater than 2%, and the "Other" group of all other CTAs. The "Other" group serves as the baseline category, so β_1 and β_2 represent the change in intercept, while β_4 and β_5 the change in AUM, of the "High" and "Low" groups relative to the "Other" group. Control variables are the yearly lagged return of the CTA, a dummy variable for a live CTA (versus dead), and the yearly return on the Standard and Poors' 500 index (SP500), the Goldman Sachs Commodity Index (GSCI), the Lehmann Brothers Aggregate Bond Index (LAB), the Stark 300 Trader CTA Index (Stark), the price of gold (Gold), and the Small Minus Big (SMB), High Minus Low (HML), and Up Minus Down (UMD) portfolios. For the dependent variable y_{it} we use, in turn, (1) the yearly compounded return, (2) the yearly compounded return in excess of the T-bill rate, which adjusts returns for a hurdle rate equal to the T-bill rate, and (3) the yearly returns volatility. If the high/low difference in fees charged by CTAs is a factor driving the size-returns-volatility relationship, then we should observe $\beta_3 < 0$ since returns and volatility both decrease with size, $\beta_1 > \beta_2$ since CTAs in the "High" group have higher returns and higher volatility than CTAs in the "Low" group[4]. We should also observe $\beta_4 < 0$

[4]The "Low" group consists of CTAs with incentive fee less than 20% and management

with $\beta_4 < \beta_5$ and possibly β_5 insignificant, since the decreasing relationship between returns and volatility with size should be stronger in the "High" group. Moreover, these effects should be present even when controlling for the market variables and the lagged return. The results of this regression, which appear in Table 3.3 for compounded returns (Model 1), compounded excess returns (Model 2), and volatility (Model 3), produce values of β_1 through β_5 that are consistent with our expectations, although some of these coefficients are not significant. In Model 2, for example, $\beta_3 = -0.899$, and $\beta_1 = 27.1$, whereas β_2 is not significantly different from zero. Moreover, $\beta_4 = -1.59$ and $\beta_5 = 0.487$. The last row of Table 3.3 presents the p-value for the test of the contrast $\beta_4 = \beta_5$. The value of $p = 0.096$ indicates that the difference between β_4 and β_5 is different from zero, significant at the 10 percent level. The coefficients for Models 1 and 3 produce similar results. This analysis points to a significant effect of fee differential on the returns-volatility-size relationship.

3.5 Size and Indexing

As CTAs grow in size, the management fees they earn on AUM become increasingly large, which might be sufficient to meet their overhead costs and earn the managers a healthy remuneration, without having to earn the incentive fee on performance. CTAs with low incentive fees show modest returns and low volatility, while those high incentive fees tend to be volatile CTAs that chase returns. CTAs with low incentive fees may have the incentive to "rest on their laurels" and become passive indexers. This might be because of complacency, reputation, or because as established CTAs they have attracted more risk-averse clients, such as pension funds. Our hypothesis is that as CTAs grow in size, they behave more like indexers and less like aggressive investors To test this hypothesis, we group CTAs into twenty size percentiles,

fee greater than 2%, and the "High" group consists of CTAs incentive fee greater than 20% and management fee less than 2%. All other CTAs are classified to the "Others" group.

from smallest to largest. In each percentile, we run a regression using excess monthly returns as dependent variable, and the return on a CTA index as predictor variables. We use, in turn, the monthly return on the Stark 300 CTA Trader Index (Stark), the Barclay BTOP 50 CTA Index (BTOP), CISDM Asset-Weighted CTA Index (CISDM), and the HedgeFund.Net CTA Index (HFNet). We run these regressions separately for CTAs in the "High" and "Low" incentive fee groups.

Table 3.4 presents the R^2 from each regression. As CTAs grow larger, their exposure to these indices increases, as evidenced by the R^2 values which tend to increase with AUM percentile. The table indicates also that the increase is particularly remarkable for funds in the "Low" incentive fee group. For example, for "Low" CTAs in the first percentiles (less than \$100K in AUM), the R^2 to the Stark Index is only 2%. By the time CTAs had grown to over \$226M (last percentile), the R^2 had increased to 36%. For CTAs in the "High" group the R^2 increased from 0.9% to 25%. The same pattern shows up for CTAs' exposure to the BTOP CTA index, and to the CISDM and HFNet indices. These results suggest that as CTAs grow in size, they behave more like indexers and have return characteristics that resemble the pack. This is particularly true for CTAs in the "Low" group, who rely mostly on their management fee to survive.

To evaluate how the increase in R^2 holds up when additional variables are introduced, we repeat the analysis of Table 3.4 on the "High" and "Low" groups, but include the control variables described in Table 2.3 in the regressions. A plot of R^2 as a function of size decile appears in Figure 3.2. Again, it indicates that the tendency to increase index exposure with size is particularly evident in the "Low" group.

Table 3.4 and Figure 3.2 suggests a positive relationship between indexing and size, so that CTAs behave more like indexers as they grow, and that this increase is particularly high for CTAs with low incentive fees. To quantify how the exposure to indexes increases, we define the dependent variable $y_i = R_i^2$ and run the regression

$$\begin{aligned} R_i^2 &= \alpha + \beta_1 High_i + \beta_1 Low_i + \beta_3 \log(AUM_i) + \beta_4 High_i \times \log(AUM_i) \\ &\quad + \beta_5 Low_i \times \log(AUM_i) + \varepsilon_i \end{aligned}$$

where R_i^2 is the the coefficient of determination from percentile i taken from Table 3.4, $High_i$ and Low_i are dummy variables for an R_i^2 originating from "High" and "Low" CTA, respectively, and $\log(AUM_i)$ is the logarithm of the mean AUM in percentile i. The "Other" group is the baseline group, so the β coefficients for the "High" and "Low" groups represent the incremental change in slope and intercept relative to the "Other" group.

The results in Table 3.5 indicate a significant and positive relationship between size and indexing, for the four indices used, and a tendency for this relationship to be stronger in the "Low" incentive fee group. The intercepts for the three groups is the same in most cases, as evidenced by the insignificant values of β_1 and β_2. In all cases, there is a strong positive effect of AUM, indicated by $\beta_3 > 0$ and significant. The slope of the "Low" group is significantly higher than that of the "Other" group, as indicated by $\beta_5 > 0$, but the slope of the "High" group is not, since β_4 is never significant. For example, the slope of the regression line with the BTOP CTA index for the "Others" group is $\beta_3 = 2.65$. The incremental increase in the slope for the "High" group is $\beta_4 = 0.448$, but this is not significant, while the increase for the "Low" group is $\beta = 1.31$, which is significant at the 5 percent level. The other indices paint a similar picture. These results suggest that the tendency for CTAs to index and behave more like their peers as they grow in size is strongest among CTAs with low incentive fees. Both groups, however, eventually engage in indexing. Hence, an alternate driver besides differences in fees is causing CTAs to index, perhaps because as they grow, CTAs hold proportionately more cash and T-bills, and invest proportionately less in futures contracts.

As an alternate measure of indexing, we examine the decrease in α brought on by an increase in size, in the "High" and "Low" incentive groups. Our hypothesis is that the decrease in alpha is more pronounced for the "Low" group. Hence, in each AUM percentile, we run the regression

$$R_t = \alpha + \beta X_t + \varepsilon_t$$

separately for both groups, where R_t is the CTA's monthly return, and X_t is a vector of explanatory variables that incudes the SP500 Index, the GSCI, the Lehmann Aggregate Bond index, the Stark 300 Index, the return on Gold, and the SMB, HML, and UMD portfolios. We then plot the estimated α versus the AUM percentile, by incentive fee. The plot, which appears in Figure 3.3, is consistent with the size-performance-fee relationship alluded to throughout this chapter. In particular, CTAs with high incentive fees and low management fees post high alpha, especially when they are small. These CTAs maintain a positive alpha throughout most of their growth phase. The alpha of CTAs with low incentive fees, however, is much worse. Those CTAs start with positive alpha, but their alpha quickly deteriorates as they grow.

3.6 Conclusion

This chapter examines the incentives of CTAs when their managers derive their compensation from a mixture of asset-based and performance-based fees. Large CTAs tend to be old and run by managers who are risk averse, especially for CTAs with low incentive fees and high management fees. Consequently, their returns are modest. This can be partly explained by the desire of their managers to preserve the capital they hold, and to preserve their reputation in response to the more conservative clients – such as pension funds – that well-established CTAs attract. The results of this chapter show that in addition to reputation effects, large CTAs become more risk averse because they derive most of their compensation from management fees. As their capital grows, their need to take on more risk and post good performance decreases, and they behave more like indexers and asset gatherers. Small CTAs, on the other hand, do not derive much compensation from their management fees, and must post good returns to earn enough compensation from their incentive fees to survive. This is especially true for small CTAs with high incentive fees and low management fees.

We do not account for a highwater mark, so our incentive payments are probably overestimated since the highwater mark would tend to lower these payments. Moreover, using the T-bill rate as the hurdle rate is conservative, which implies that the excess returns we use to calculate profits and flows are probably too high. Nevertheless, since our goal is to examine the incentives for capital growth introduced by a two-tier fee ratio, we do not believe these biases to be overly important.

In general, CTAs charge fixed fees, and these fees do not vary across clients. Large clients, such as institutional investors, will have bargaining power over the fees, since they usually inject a large amount of capital into the CTA. Moreover, some CTAs and hedge funds have been lowering their fees, to differentiate themselves in light of increased competition in the alternative investments industry. The effect of fee variation on our results, and the change in risk a CTA would experience given a large inflow of investor capital, are issues for further research.

Having examined hedge fund liquidation and incentives, we now focus attention on operational risk. Loose regulation in the hedge fund and CTA industry, coupled with a lack of transparency, implies that hedge funds and CTAs are at high risk of failure from operational events when economic conditions deteriorate, when their managers experience a run of bad luck, or because of fraud. Indeed, Capco (2003) attribute 50 percent of all hedge fund failures to operational risk. Brown et al. (2007) find that regulatory information reported by hedge funds can help predict operational events.

Investors are concerned with the operational risk that their hedge funds are exposed to, but unfortunately hedge fund and CTA databases do not provide the reason behind liquidation. Hence, information on operational events must be acquired from other sources. In the following chapter, we examine operational risk in the banking sector, and show how operational losses, especially those due to fraud, are dependent upon the economic climate during which the losses were incurred.

Table 3.1. Description of CTA Characteristics

Mean, median, standard deviation, minimum and maximum values of variables used in the analysis. Monthly Return is the monthly return, expressed as a percent, Yearly Volatility is the yearly volatility of returns, expressed as a percent, Management Fee and Incentive Fee are the management fee and the incentive fee, respectively, each expressed as a percentage. Age is the age of the CTA in years, StdDev is the yearly standard deviation of returns, expressed as a percentage, and AUM is the monthly assets under management, expressed in $M. The last three rows are AUM by incentive fee. "High Fee" are CTAs with incentive fee greater than 20% and management fee less than 2%. "Low Fee" are CTAs with incentive fee less than 20% and management fee greater than 2%. "Others" are all other CTAs. Numbers in parentheses in the last three rows are the number of CTAs in each incentive fee category. Returns are expressed net of all fees.

	Mean	Median	Std Dev	Min	Max
Monthly Return (%)	1.31	0.44	9.20	−202.00	377.50
Yearly Volatility (%)	22.63	16.79	22.78	0.02	460.43
Management Fee (k_m)	2.16	2.00	1.58	0.00	30.00
Incentive Fee (k_i)	19.70	20.00	5.31	0.00	50.00
Age (Years)	5.48	4.17	4.52	0.08	31.00
AUM ($M)	55.3	4.4	326.8	0.01	27,102
AUM by Incentive Fee					
High Fee (124)	35.5	2.9	114.93	0.06	2,680
Low Fee (136)	23.8	3.2	73.5	0.1	9,520
Others (2,192)	59.5	4.7	349.4	0.01	27,102

Table 3.2. Mean Monthly Return and Volatility by Incentive Fee and by Size Decile

CTAs in the "High", "Low", and "Others" categories are grouped into deciles according to their average assets under management (AUM), and the mean monthly return and monthly standard deviation of returns is obtained in each size decile. AUM1 through AUM10 are deciles for average annual assets. "High" are CTAs with incentive fee greater than 20% and management fee less than 2%. "Low" are CTAs with incentive fee less than or equal to 20% and management fee greater than or equal to 2%. "Others" are all other CTAs. "All" are all CTAs grouped together, regardless of fees.

	Returns				Volatility			
	High	Low	Others	All	High	Low	Others	All
AUM1	5.19	2.34	2.66	2.42	15.08	9.55	11.47	9.93
AUM2	3.46	1.64	2.01	1.73	9.36	8.12	8.89	8.27
AUM3	2.63	1.45	1.56	1.51	11.86	7.43	6.83	7.43
AUM4	1.41	1.45	1.62	1.49	5.85	7.22	5.84	6.86
AUM5	0.64	1.21	0.97	1.13	4.79	6.33	5.66	6.10
AUM6	1.07	1.13	1.04	1.11	5.96	5.71	5.97	5.79
AUM7	1.17	1.02	1.03	1.03	7.45	5.39	5.00	5.31
AUM8	1.67	1.06	0.98	1.05	6.09	5.33	4.93	5.22
AUM9	1.04	0.68	0.97	0.78	4.71	4.54	4.48	4.52
AUM10	1.22	0.72	0.63	0.71	5.31	4.19	3.87	4.13

Table 3.3. Regression of Returns and Volatility on CTA Characteristics and Market Variables

Regression of CTA yearly compounded returns (Model 1), yearly compounded excess returns (Model 2) in excess of the monthly T-bill rate, and yearly volatility (Model 3). "High Incentive Fee" are CTAs with an incentive fee greater than 20% and with a management fee less than 2%. "Low Incentive Fee" are CTAs with incentive fee less than 20% and management fee greater than 2%. Log(AUM) is the logarithm of the yearly average AUM, Ret_{t-1} is the one-year lagged compounded return, and Active is a dummy variable with value one if the CTA is active. SP500, GSCI, LAB, and Stark are the one-year compounded return on the S&P 500 Index, the Goldman Sachs Commodity Index, the Lehmann Brother Aggregate Bond Index, and the Stark 300 CTA Index, respectively. Gold is the yearly compounded return on gold, and SMB, HML, and UMD are the yearly compounded return on the Small Minus Big, High Minus Low, and Up Minus Down portfolios, respectively. Entries are estimated regression coefficients, where ***, **, and * denote significance at the one, five, and ten percent level, respectively. The last row is the p-value for the test that $\beta_4 = \beta_5$.

	Model 1 CompRet	Model 2 Comp ExRet	Model 3 Volatility
Intercept (α)	6.43***	7.13***	9.34***
High Incentive Fee (β_1)	21.7**	21.7**	4.76***
Low Incentive Fee (β_2)	−7.13	−6.26	1.22
Log(AUM) (β_3)	−0.893***	−0.899***	−0.531***
High Incentive Fee×Log(AUM) (β_4)	−1.57	−1.59	−0.300**
Low Incentive Fee×Log(AUM) (β_5)	0.515	0.487	−0.037*
Ret_{t-1}	0.149***	0.157***	0.026***
Active	7.67***	7.19***	0.402***
SP500	0.207	−0.265***	−0.015***
GSCI	−0.003	−0.069***	−0.001
LAB	0.034	−0.212**	0.008
Stark	0.660***	0.689***	0.054***
Gold	−0.070*	0.109***	−0.009
SMB	−0.075	−0.542***	−0.013**
HML	0.047	−0.007	−0.008
UMD	0.053	−0.245***	−0.011*
p-value for $\beta_4 = \beta_5$	0.096	0.097	0.149

Table 3.4. Indexing and Size

Exposure of CTAs to commodities and bond indices, by assets under management (AUM). CTAs are classified into twenty size percentiles and into two incentive fee groups. "High" are CTAs with incentive fee greater than or equal to 20%, and management fee less than or equal to 2%. "Low" are CTAs with incentive fee less than 20% and management fee greater than 2%. For funds in each percentile-group classification, the regression $r_t^e = \alpha + \beta Index_t + \varepsilon_t$ is run, where r_t^e is the fund's monthly return in excess of the monthly T-Bill rate, and $Index_t$ is the monthly value of, in turn, the Stark 300 Trader Index (Stark), the Barclay BTOP Top 50 CTA Index (BTOP), the CISDM Asset-Weighted CTA Index (CISDM), and the HedgeFund.Net CTA index (HFNet). Entries are the R^2 from each regression, expressed as a percentage.

		Stark		BTOP		CISDM		HFNet	
Percentile	AUM ($M)	Low	High	Low	High	Low	High	Low	High
1	< 0.1	2.0	0.9	1.9	0.7	2.1	1.0	2.1	1.0
2	0.1 to 0.2	11.7	3.4	11.1	3.2	11.6	3.3	10.7	3.7
3	0.2 to 0.3	6.2	1.7	5.7	2.0	7.1	1.8	6.4	1.9
4	0.3 to 0.5	4.6	3.1	3.8	2.9	3.9	3.3	3.8	3.1
5	0.5 to 0.9	5.7	7.2	4.0	6.0	5.4	6.8	6.4	7.1
6	0.9 to 1.2	16.7	5.3	17.0	4.6	17.5	5.3	18.7	5.5
7	1.2 to 1.7	7.1	8.8	8.0	7.5	7.9	8.3	9.0	8.6
8	1.7 to 2.2	6.7	9.2	7.5	8.3	6.9	8.5	7.6	9.2
9	2.2 to 3.1	15.7	7.6	14.3	7.3	16.7	7.4	14.2	7.6
10	3.1 to 4.4	7.0	7.0	7.8	6.8	7.5	7.1	7.7	7.5
11	4.4 to 6.1	8.6	11.3	7.6	11.1	9.1	11.0	10.8	11.4
12	6.1 to 8.7	31.6	10.3	31.2	9.9	32.9	10.2	32.8	10.7
13	8.7 to 12.0	15.6	10.3	19.8	9.4	18.0	10.1	18.8	11.0
14	12.0 to 17.4	38.5	14.6	36.5	13.4	36.6	14.7	38.8	15.2
15	17.4 to 25.0	23.0	20.8	19.6	20.1	21.9	20.0	22.3	19.8
16	25.0 to 38.0	26.7	20.0	24.5	17.3	26.6	18.7	27.8	19.2
17	38.0 to 58.3	21.0	20.0	23.4	18.3	21.4	19.2	21.9	19.7
18	58.3 to 98.2	28.2	24.2	29.7	22.5	28.9	24.0	27.1	25.1
19	98.2 to 226.7	25.5	22.3	31.6	20.7	27.1	22.1	22.9	21.6
20	>226.7	36.1	25.1	29.7	24.4	34.3	25.2	27.7	23.7

Table 3.5. Indexing and Size Regressions

Regression $R_i^2 = \alpha + \beta_1 High_i + \beta_1 Low_i + \beta_3 \log(AUM_i) + \beta_4 High_i \times \log(AUM_i) + \beta_5 Low_i \times \log(AUM_i) + \varepsilon_i$, where R^2 is the coefficient of determination in size percentile i, obtained from Table 3.4, $High_i$ and Low_i are dummy variables for an R_i^2 originating from the "High" and "Low" incentive fee groups, respectively, and $\log(AUM_i)$ is the logarithm of mean assets in percentile, $i = 1, .., 20$. The indices are, in turn, the Stark 300 Trader Index (Stark), the Barclay BTOP 50 CTA Index (BTOP), the Lehmann Aggregate Bond Index (LAB), and the Salomon Smith Barney World Government Bond Index (SSB). Entries are estimated values of the coefficients from each regression. Coefficients denoted with ***, **, and * denote significance at the one, five, and ten percent. T-statistics for each coefficient are in parentheses.

Index	Intercept α	High Fee β_1	Low Fee β_2	Log(AUM) β_3	High×AUM β_4	Low×AUM β_5
Stark	-13.1^{***}	-3.01	-3.45	2.58^{***}	0.698	1.37^{**}
	(-3.3)	(-0.5)	(-0.6)	(5.6)	(1.1)	(2.1)
BTOP	-13.3^{***}	-2.07	-3.44	2.65^{***}	0.448	1.31^{**}
	(-3.6)	(-0.4)	(-0.7)	(6.2)	(0.7)	(2.2)
LAB	-0.875	-0.885	-2.04^{*}	0.175^{*}	0.160	0.307^{**}
	(-1.1)	(-0.8)	(-1.8)	(1.9)	(1.2)	(2.4)
SSB	-1.23	-0.943	-1.73	0.262^{**}	0.119	0.259^{*}
	(-1.3)	(-0.7)	(-1.3)	(2.4)	(0.8)	(1.7)

Figure 3.1. Returns, Volatility, and Assets for High and Low Incentive Fee CTAs

Mean monthly return as a function of assets under management (AUM). CTAs are separated according to their fees. CTAs with incentive fee greater than 20% and with management fee less than 2% are the "High Incentive Fee" group (solid lines), and CTAs with incentive fee less than or equal to 20% and with management fee greater than or equal to 2% are the "Low Incentive Fee" group (dashed lines). Each year, the AUM of CTAs in each group are divided into deciles, and the mean monthly return and mean monthly standard deviation are obtained in each decile. Returns are represented with circles and volatility with squares.

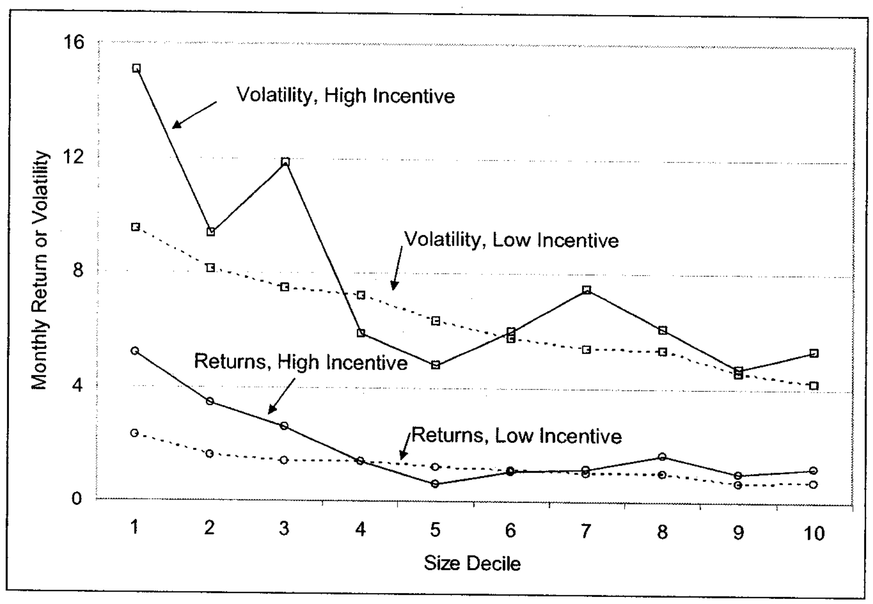


Figure 3.2. Indexing and Size, High and Low Incentive Fees

Exposure of CTAs to commodities and bond indices, by assets under management (AUM). Funds are classified into twenty AUM percentiles. For funds in each percentile, the regression $R_t^e = \alpha + \beta X_t + \varepsilon_t$ is performed, where R_t^e is the fund's monthly return in excess of the monthly T-Bill rate, and X_t is a vector of explanatory variables that includes the value at month t of the S&P 500 index, the Goldman Sachs Commodity Index, the Lehmann Aggregate Bond Index, the return on gold, and the yearly compounded return on the Small Minus Big, High Minus Low, and Up Minus Down portfolios. "High Incentive Fee" are CTAs with incentive fee greater than or equal to 20% and management fee less than or equal to 2%, and "Low Incentive Fee" are CTAs with incentive fee less than 20% and management fee greater than 2%.

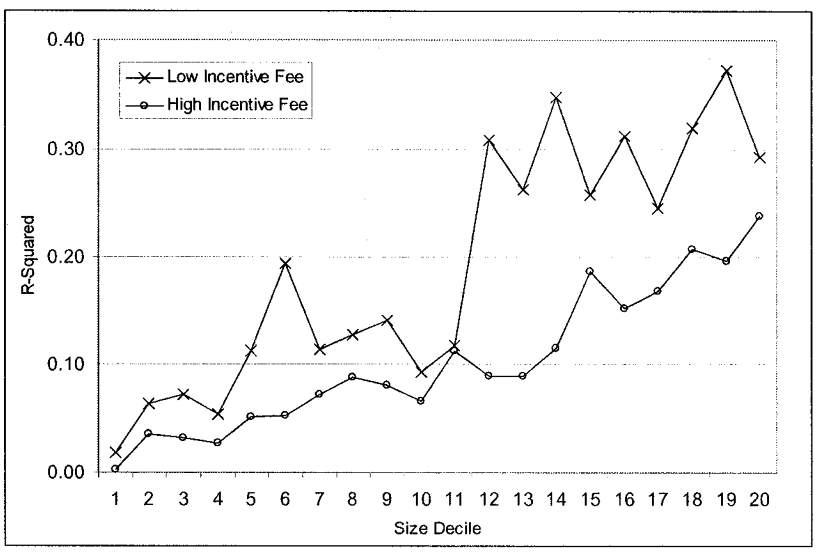
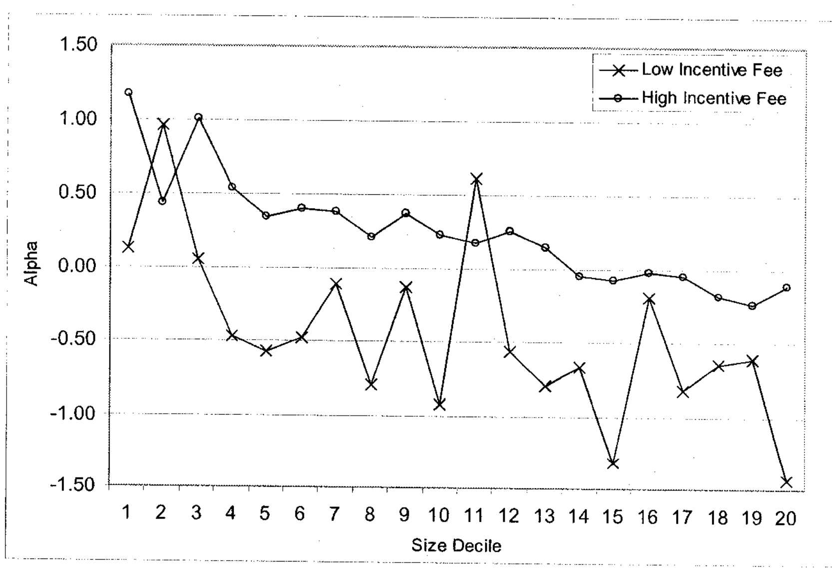


Figure 3.3. Alpha and Size, High and Low Incentive Fees

Exposure of CTAs to the Barclay BTOP Top 50 CTA Index, by assets under management (AUM). Funds are classified into twenty AUM percentiles. For funds in each percentile, the regression $R_t = \alpha + \beta X_t + \varepsilon_t$ is performed, where R_t is the CTA's monthly return, and X_t is a vector of explanatory variables that incudes the SP500 Index, the GSCI, the Lehmann Aggregate Bond index, the Stark 300 Index, the return on Gold, and the SMB, HML, and UMD portfolios. Plots are estimated α versus size AUM percentile, by incentive fee. "High Incentive Fee" are CTAs with incentive fee greater than or equal to 20% and management fee less than or equal to 2%, and "Low Incentive Fee" are CTAs with incentive fee less than 20% and management fee greater than 2%.



CHAPTER 4

FRAUDS AND MACROECONOMIC CYCLES

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4.1 Introduction

In this chapter we link operational losses to macroeconomic conditions. We show that operational losses are dependent on the economic climate under which the losses were incurred, so that losses increase during periods of high unemployment and low growth in real Gross Domestic Product (GDP), and decrease during other periods. We show that this dependency is especially evident for fraudulent losses from financial firms such as banks, thrifts, investment companies, and brokerage firms. The results of this chapter show that the capital charge calculated by banks for operational losses should account for macroeconomic cycles.

4.2 Literature Review

The Basel Committee on Banking Supervision (BCBS) was created to homogenize banking practices around the world, and has called upon banks to adopt standardized approaches for all aspects of banking, such as risk management, capital charge, and supervision. Because of the flexibility allowed by the BCBS for calculating capital charge, much of the literature deals with developing models to quantify capital charge. Pezier (2002) suggests using firm size as one exposure indicator for capital charge. Operational losses are linked to firm size by Cruz (2002). In a cross-sectional regression, over ninety percent of variability in operational losses can be explained by firm variables such as system downtime, number of transactions, data quality, and firm size. Shih, Samad-Khan, and Medapa (2000) also find a positive relation between the size of the firm and the size of operational losses. Nearly ten percent of the variability in operational losses experienced by firms can be attributed to revenue alone.

While no study examines the relationship between economic conditions and operational losses, several studies show a strong relationship between fraud, corporate governance, and business cycles. Philippon (2005) shows that the profits of poorly-governed firms are more susceptible to variation from business cycles. Kedia and Philippon (2005) show that firms with weak governance are more likely to commit fraud, and that fraud is more likely to occur during periods of economic expansion. Their finding is not contrary to our hypotheses, however, since fraudulent losses are not realized until times are bad. Indeed, Povel, Singh, and Winton (2005) show that while manager-perpetrated fraud peaks toward the end of economic expansions, frauds are revealed only in the recessions that follow. During periods of good economic conditions and high profits there is low monitoring by investors, so it is easier for managers to hide fraud. When economic conditions change for the worst, monitoring increases and fraudulent activity is exposed. We bridge the gap between the literature on operational risk and corporate governance by considering the effects of economic conditions on financial firms and their operational losses.

Much of the research in operational risk is directed towards adapting actuarial models to calculate capital charge under the Loss Distribution Approach (LDA). Haubenstock (2000) argues that actuarial models are becoming the industry standard for measuring capital charge. Samad-Khan and Gittleson (1998) explain that actuarial models are appealing because they model low-frequency and high-severity events, and because frequency and severity can be estimated separately. In addition, they are consistent and comparable with value at risk models. Frachot and Roncalli (2001) describe the theoretical foundations for LDA, while Frachot, Moudoulaud, and Roncalli (2003) discuss how LDA can be implemented in practice. Aït-Sahalia and Lo (2000) develop a value-at-risk (VaR) measure that allows for differences in economic valuation, such as differences in risk aversion and time preferences.

Empirical studies that apply the LDA to estimate capital charge for operational losses include those of de Fontnouvelle, DeJesus-Rueff, Jordan, and Rosengreen (2003), de Fontnouvelle and Rosengreen (2004), Chapelle, Crama, Hübner, and Peters (2005), and Hübner, Peters, and Plunus (2005). We evaluate whether parameter estimates used as inputs in LDA models are sensitive to economic conditions under which the losses were incurred. High sensitivity of parameters implies that the capital charge obtained under the LDA would change when economic conditions deteriorate.

Any finding that operational risk losses are contagious across the business of banks would lend support to the findings on international correlation and contagion. Longin and Solnik (2001) use extreme value theory to show that correlations across international equity markets increase during bear markets, but not during bull markets. Kho, Lee, and Stultz (2000) show that banks exposed to countries suffering financial crises experience larger losses than unexposed banks. When banks are exposed to countries benefiting from bailouts, however, they experience larger gains than unexposed banks. That these banks experience losses and gains as a group lends support to the contagion hypothesis.

Contagion is implied by the Standardized Approach, since the approach assumes perfect dependence between the fifty-six event type/business line combinations. It is possible, however, that losses from different business lines, and those caused by different events, could be less than perfectly dependent. A reduction in dependence is appealing because it leads to a reduced capital charge. Chapelle, Crama, Hübner, and Peters (2004) show that the correlation between the frequencies of losses across business lines are all under 0.50, and that capital charge is reduced by roughly one-third when less than perfect dependence is introduced. In this chapter we show that the dependency of operational losses to deteriorating economic conditions is present across most business lines of international banks. Models that assume less than perfect dependence across business lines, therefore, need to be adjusted for changing market conditions.

4.3 Data

We use operational risk losses recorded in the OpVantage/OpVar database over the December 31, 1972 to January 10, 2005 period. We focus on losses from U.S. firms, and on losses from international banks. Table 4.1 presents a brief description of these losses. There are 7,892 recorded losses for U.S. firms, with an average loss of US$69.8 million (expressed in 2004 dollars). Most of the losses are due to clients, products, and business practices, but the largest losses are from business disruptions and system failures. The distribution of losses is highly positively skewed in all event types, and shows high variability. When divided by business line, international banks suffered the greatest number of losses in retail banking. The largest losses, however, were from commercial banking and trading and sales. In this chapter we also focus on the 3,043 losses experienced by U.S. financial firms. These losses are expressed in 2004 dollars using the monthly rate of inflation calculated from the Consumer Price Index reported by the U.S. Department of Labor (www.inflationdata.com).

Periods of expansion and recession are obtained using business cycle dates from the National Bureau of Economic Research (www.nber.org). Recessions over the time period covered by the data used this chapter are defined by NBER to have occurred from November 1973 to March 1975, from January 1980 to July 1980, from July 1981 to November 1982, from July 1990 to March

1991, and from March 2001 to November 2001. Dates of bear markets and bull markets are from Ned Davis Research, Inc. (www.ndr.com). The U.S. monthly unemployment rate is obtained from the U.S. Department of Labor, Bureau of Labor Statistics (www.bls.gov). The real U.S. gross domestic product (GDP) is from the U.S. Department of Commerce, Bureau of Economic Analysis (www.bea.doc.gov). Yearly data on bankruptcies are from the U.S. Courts (www.uscourts.gov). Market capitalization of firms is obtained from CRSP (www.crsp.chicagogsb.edu).

Descriptive statistics for the variables used in this chapter appear in Table 4.2. The firms in our sample have an average market capitalization of over $US6.4B. The scaled loss is the logarithm of the loss divided by market capitalization. Since this ratio is less than one, the log is negative. Statistics on the U.S. economic variables are consistent for the period under consideration. For example, annual real U.S. GDP increased by an average of 3.08 percent over the period, with the biggest increase experienced in 1984. There was an average of 857,996 personal bankruptcies over the period, with a maximum of over 1.6 million bankruptcies experienced in 2003. Correlations between yearly values of the independent variables used in the regressions appear in Table 4.2 also. These correlations are consistent with our expectation of increased losses during bad economic conditions. Hence, we find losses to be positively and significantly related to unemployment and bankruptcies, and negatively related to growth in real GDP.

The basic relationship between operational losses and economic conditions is illustrated in Figure 4.1. For each firm, every year we average the firm's losses and express these losses as a proportion of the firm's market capitalization. Figure 4.1 presents a time-series plot of these proportional losses, overlapped with light and dark shaded areas, which represent periods of recessions and of bear markets respectively. It shows a tendency for losses to occur during periods of bad economic conditions. For example, there are spikes near the crash of October 1987, near the bear markets of late 1998, and near the recession of 2001 and the bear market of late 2002. The graph illustrates that losses tend to increase during bad times, and serves to motivate more formal analyses of the relationship between losses and economic conditions. The graph also suggests that losses from financial firms are especially sensitive to recessions and bear markets.

4.4 Methods and Results

In this section we describe the methods we use to test our hypothesis of a link between operational losses and economic conditions, and we provide the results of our analyses. Table 4.3 presents statistics on scaled losses during periods of economic crises, for all operational losses experienced by U.S. financial firms, and for the subset of losses arising from fraudulent activities only. The scaled loss is the loss divided by firm capitalization. The distribution of losses are heavily skewed to the right in all regimes. Hence, we focus on median scaled losses. We compare losses in each group using the Kruskal-Wallis test.

The results in Panel A suggest that median scaled losses from U.S. financial firms were higher during periods of bad economic conditions than during good periods. For example, during periods of low real GDP growth, the median scaled loss was 18.6, but during periods of high real GDP, the median loss was 4.2, a difference which is significant ($p = 0.0001$). During periods of high and low unemployment the median scaled losses were 14.2 and 7.3 ($p = 0.0055$). When median scaled losses are compared across periods of NBER expansion and contractions the differences are insignificant, possibly due to the small number of losses during recessions. When fraudulent losses are compared across good and bad economic periods, however, the results are much weaker. Only during periods of low real GDP growth were fraudulent losses significantly lower ($p = 0.0001$). Hence, in this simple analysis, we find sparse evidence that the size of losses increases during periods of bad economic conditions, whether all scaled losses (Panel A), or only scaled losses arising from external or internal fraud (Panel B), are considered.

4.4.1 Relating Economic Conditions to Operational Losses

We wish to investigate whether scaled losses are related to economic conditions, and whether losses due to internal fraud react differently to economic conditions than losses due to external fraud. The scaled loss is defined as the log of the loss divided by the average market capitalization of the firm during the year the loss was incurred. Each year, we aggregate the scaled losses for each firm, which produces a yearly scaled loss for every firm in the sample. To investigate whether losses experienced by financial firms are more sensitive to macroeconomic conditions than losses experienced by non-financial firms, we fit the linear regression model

$$Y_{it} = \alpha + \beta_X X_t + \beta_F Fin_i + \beta_{FX} Fin_i \times X_t + \varepsilon_{it} \qquad (1)$$

where Y_{it} is the yearly aggregated scaled loss of firm i during year t, and where X_t is in turn, the raw change in real GDP during year t, and the unemployment rate in year t. Lagged values of these macroeconomic variables are defined as one-year lags. The variable Fin_i is a dummy variables that take on the value one if firm i is a financial firm, and zero otherwise. The results, which appear in Table 4.4, indicate that losses tend to increase during bad times, and decrease during good times. In particular, we find a link between scaled losses and raw change in real GDP and unemployment. The coefficient for GDP lagged change is negative, which indicates that scaled losses tend to increase when past growth in real GDP is low, and the coefficient for unemployment is consistently positive, which indicates that losses tend to increase with unemployment. Moreover, the interaction term β_{FX} indicates that the sensitivity of losses to macroeconomic conditions is more pronounced for financial firms. Hence, operational losses increase during bad times, and this increase is more dramatic for financial firms than for non-financial firms.

Our next hypothesis is that losses due to fraud are more sensitive to economic conditions than other types of losses. During bad times, individuals may experience personal hardship – such as the loss of a job, the forced sale of a home, or some other financial disaster – that could motivate them to commit fraud they might not otherwise commit during good times. To investigate the possibility, we fit the model

$$Y_{it} = \alpha + \beta_X X_t + \beta_F Fraud_{it} + \beta_{FX} Fraud_{it} \times X_t + \varepsilon_{it} \quad (2)$$

where $Fraud_{it}$ is a dummy taking the value one if the scaled loss from firm i during year t is due to fraud, and zero otherwise. The results appear in Panel A of Table 4.5 for all U.S. firms, and in Panel B of Table 4.5 for all U.S. financial firms. Again, we see a strong relationship between scaled losses and macroeconomic conditions. Indeed, the β_X coefficient is positive for unemployment, and negative for growth in real GDP. The interaction term β_{FX} indicates that fraudulent losses are more sensitive to economic conditions than non-fraudulent losses. When economic conditions decline, an onslaught of personal financial hardship might trigger individuals to commit fraud, which would increase fraudulent losses experienced by firms. In regressions (1) and (2) we also added the explanatory variable for personal bankruptcies, to control financial hardship experienced by individuals. The results of Tables 4.4 and

4.5 did not change much.

We wish to investigate whether or not financial firms are more at risk of internal fraud, than they are of external fraud, which would imply that financial firms are at risk of fraud from insiders, but not from outsiders. This point can be rationalized in terms of technology. It is easier for employees in financial firms to commit fraud, since they have access to the computer and financial systems of the firm. These systems are well protected from the outside, so it is difficult for outsiders to commit fraud. For non-financial firms, fraud manifests itself more in terms of contracts and relations with suppliers and customers, who do not have access to the operations of the firm. To test whether financial firms are more at risk of internal fraud than external fraud when economic conditions deteriorate, we fit the model

$$Y_{it} = \alpha + \beta_X X_t + \beta_{IF} IF_{it} + \beta_{EF} EF_{it} + \beta_{IFX} IF_{it} \times X_t + \beta_{EFX} EF_{it} \times X_t + \varepsilon_{it}$$

where IF_{it} is a dummy variables that take on the value one if the loss from firm i in year t was due to internal fraud, and EF_{it} is a dummy variable similarly defined for external fraud. Our hypothesis is that economic conditions affect internal fraud and external fraud differently for financial firms. This suggests a possible interaction between economic conditions and internal and external fraud. Hence in this regression we include the interactions between X_t and IF_{it}, and between X_t and EF_{it}, respectively.

The results of this regression appear in Panel C of Table 4.5. The coefficients β_{IF} are significant, but the β_{EF} are not significant, which indicates that most of the fraud committed on financial firms originates from internal fraud. We also find internal fraud to be more cyclical than other losses experienced by U.S. financial firms, as evidenced by the values of the β_{IFX} coefficients.

This lends support to the claim that financial firms are especially hit with fraud from insiders, but less by outsiders. We also find non-financial firms to be more affected by external fraud than by internal fraud, but none of the coefficients in those regressions are significant (results not shown).

4.4.2 Relating Economic Conditions to Operational Losses Across Lines of Business

The BCBS has expressed concern that the different lines of businesses operated by international banks could suffer losses at the same time. If so, it would imply that banks could not diversify away their losses across their business lines, and that on the contrary, these business lines would be subject to contagion. To investigate this possibility, we fit the model

$$Y_{it} = \alpha + \beta_X X_t + \varepsilon_{it}$$

across five lines of business (Asset Management, Commercial Banking, Retail Banking, Retail Brokerage, and Trading & Sales) where X_t is in turn, the raw change in real GDP during year t, the unemployment rate in year t, and their one-year lagged values. The results, which appear in Table 4.6, indicate that all lines of business are susceptible to an increase in losses when economic conditions deteriorate. This implies that a common macroeconomic factor across business lines causes the correlation between the lines to increase during bad times. Hence, models for capital charge that incorporate a less than perfect dependence of operational losses across business lines must not ignore the fact that these business lines are all sensitive to changing economic climates.

4.4.3 Relating Economic Conditions to Capital Charge

The finding that losses could increase when economic conditions deteriorate and contagion sets in, could impact capital charge calculations. Our hypothesis is that banks will need to increase their capital charge during bad economic times, so we wish to show that the loss severity will be higher during bad periods than during good periods. The first step is to select an appropriate loss distribution to estimate losses under both regimes. We choose the Pareto, Lognormal, and Inverse Gaussian distributions (Hogg and Klugman, 1984; Seshadri, 1999). The Basel Committee on Banking Supervision (BCBS) has mandated that under the Advanced Measurement Approach, capital charge of international banks is to be calculated separately for each of fifty-seven possible event type-business line combinations (seven events and eight lines). To conserve space, we estimate capital charge only on one such combination, the internal fraud event on the retail banking line, since that combination had the largest sample size by far. In each period of good and bad economic conditions, we estimate the parameters of each distribution and calculate the 99 and 99.5 percentiles. We then compare how well each distribution fits the tail of observed losses.

We use the form of the Inverse Gaussian distribution described in Seshadri (1999). For a sample of size n, the log-likelihood $\ell(\mu, \lambda)$ is proportional to

$$\ell(\mu, \lambda) \propto \frac{n}{2} \log \lambda + \frac{n\lambda}{\mu} - \frac{n\lambda\overline{x}}{2\mu^2} - \frac{n\lambda\overline{x}_{-}}{2}$$

where $\overline{x} = \frac{1}{n}\sum x_i$ and $\overline{x}_{-} = \frac{1}{n}\sum 1/x_i$. The maximum likelihood estimators are $\widehat{\mu} = \overline{x}$ and $\widehat{\lambda^{-1}} = \frac{1}{n}\sum(1/x_i - 1/\overline{x})$. The maximum likelihood estimators for the lognormal distribution are $\widehat{\mu} = \overline{x}$ and $\widehat{\sigma}^2 = \frac{1}{n}\sum(\log x_i - \phi)^2$ where $\phi = \frac{1}{n}\sum \log x_i$. The probability density function of a Pareto random variable x is given by

$$f(x) = \frac{\alpha\lambda^{\alpha}}{(x+\alpha)^{\alpha+1}},$$

for $\alpha > 0, \lambda > 0$, and $x > 0$. The maximum likelihood estimators have no closed form solution and are estimated numerically.

Table 4.7 presents the percentiles for losses due to internal fraud from the retail banking lines of international banks, under different economic regimes, bad and good, and under all regimes. The good regimes are defined as periods of low unemployment or high growth in real GDP, and the bad regimes as periods of high unemployment or low GDP growth. In each regime we obtain the empirical percentiles from the histogram of losses, and we estimate the parameters of the distributions – Pareto, Lognormal, and Inverse Gaussian – by maximum likelihood. Of the three distributions considered, the Pareto provides the best fit of the data. In all cases, we see that an increase in the percentiles occurs during a bad period. For example, the empirical 99.5 percentile during periods of high GDP is \$256 million (Panel A). During periods of low GDP, it increases dramatically, to \$1,241 million. Under all regimes, the percentile is \$756 million. Similar increases are reported for periods of high unemployment. Percentiles derived from the Pareto (Panel B), lognormal (Panel C) and Inverse Gaussian (Panel D) distribution point to the same pattern of larger losses during periods of high unemployment and during periods of low GDP growth. Hence, according to the percentiles, the loss distribution is more skewed during bad regimes than during good regimes. A loss distribution model that aggregates all losses as though they originate from the same regime will underestimate this skewness.

To compare the parameters of each distribution under the good and bad regimes, we use the following likelihood ratio test. We estimate the parameters of the Pareto distribution using losses incurred during a bad regime, and use those parameter values to calculate the likelihood with the losses incurred during a good regime, which produces the restricted likelihood. We then estimate the parameters using losses from the good regime and obtain the unrestricted likelihood. The p-value from the likelihood ratio test appears in the rightmost column of Table 4.7. It indicates that the difference in parameters between the unemployment and GDP regimes is almost always significant. This lends support to our findings, and suggests that the change in parameter values is due to real changes in loss magnitude, and not to sampling variability.

Loss distributions under bad regimes have thicker tails, which has an impact on capital at risk (CaR) calculations because these calculations use percentiles obtained from simulated losses. Under the Loss Distribution Approach, banks can calculate CaR by choosing a discrete distribution for the frequency of losses and a non-negative continuous distribution for the severity of each loss, and forming a random sum to represent aggregate losses. Frachot, Moudoulaud, and Roncalli (2003), de Fontnouvelle, DeJesus-Rueff, Jordan, and Rosengreen (2003), and Chapelle, Crama, Hübner, and Peters (2004), calculate capital charge as a percentile of the distribution of simulated aggregate losses given by $S = X_1 + X_2 + \cdots + X_N$, where S is the simulated loss, N is the yearly frequency of losses, and X_i is the amount of each loss, $i = 1, 2, \cdots, N$. The amount X_i is simulated using a distribution whose parameters have been estimated with losses incurred under a variety of economic climates. The results in Table 4.7, however, suggest that capital charge be calculated by taking into account the economic climate under which the losses were incurred. The loss amount X_i should be simulated using parameters estimated under different regimes, since these parameters are not constant across regimes. Since the percentiles in Table 4.7 are larger during bad times, the capital charge during bad times will be larger than the capital charge during good times.

4.5 Conclusion

In this chapter we link operational losses to macroeconomic conditions. We find that scaled losses due to operational events tend to increase during periods of high unemployment, and during periods of low growth in real GDP. We have attempted to include as many losses as possible from U.S. firms, but some losses are likely never reported. This is especially true for banks, given the large level of accounting discretion these institutions enjoy. In this database there is considerable clustering of losses on December 31st of each year prior to 2001, likely because the exact day and month of the loss was unknown. To remove the clustering, we randomly assign a month for each loss in those years. This was done on 2,029 of 3,043 (67 percent) losses from U.S. financial firms, and on 2,065 of 3,222 (64 percent) losses from international banks. Eliminating losses prior to 2001 would have drastically reduced our sample size. Since most of our analyses are performed using yearly aggregated losses, clustering is not likely to affect the results of this chapter. For the analysis of percentiles, which rely on monthly data for unemployment and on quarterly data for real GDP, we have randomly assigned a month to all losses prior to 2001, which removes clustering. In keeping the clustered losses, we are not biasing the results favorably but rather diluting the economic effects that we observe.

Our data is longitudinal, but unfortunately we do not have balanced panel data since we do not have the same firms showing up every year in the data. The effect of losses on GDP could be due to a time effect, since both losses and real GDP are increasing over the observation period. As a robustness check, we included year dummies in all the regressions, but most of these dummies were not significant. By using change in real GDP rather than the level of GDP, we are effectively removing any time trend inherent in this series.

We find a link between losses and economic conditions under which the losses were incurred. In particular, losses increase during bad economic regimes, and decrease during good regimes. Similar to de Fontnouvelle, DeJesus-Rueff, Jordan, and Rosengreen (2003), we find considerable variation in the parameters driving the loss distributions, so that during bad regimes the percentiles of the loss distribution are inflated. Using the Pareto distribution, for example, the 99th percentile under low GDP growth is roughly 6 times large than under high GDP growth. Like de Fontnouvelle and Rosengreen (2004) and Chapelle, Crama, Hübner, and Peters (2005), we find a heavy-tailed distribution (the Pareto) to provide the best fit to the data. Other distributions have tails which are too light to account for extreme losses.

Table 4.1. Descriptive Statistics of Losses From U.S. Firms and International Banks

Number of losses, mean loss, median loss, and standard deviation of losses in OpVar database, in $US million, from 1973 to 2004 inclusive. PANEL A: Losses of U.S. firms, by event type. PANEL B: Losses of international banks, by business line.

PANEL A: By Event Type	Number	Mean	Median	Std Dev
Business Disruption & System Failures	39	126.1	35.8	234.6
Client Products & Business Practices	4,838	90.5	9.7	1,347.2
Damage to Physical Assets	253	69.0	8.3	524.9
Employment Practices & Work Safety	693	40.4	6.0	307.4
Execution Delivery & Process Mngmt	451	33.2	5.1	150.6
External Fraud	519	25.1	5.6	70.3
Internal Fraud	1,099	31.3	5.1	120.6
All Losses Combined	7,892	69.8	7.9	1,065.1

PANEL B: By Business Line	Number	Mean	Median	Std Dev
Agency Services	84	54.1	11.6	120.4
Asset Management	262	59.8	10.1	152.9
Commercial Banking	685	131.1	13.8	842.3
Corporate Finance	120	72.5	12.4	277.7
Payment & Settlement	39	29.0	6.9	51.7
Retail Banking	1,217	38.8	6.3	158.9
Retail Brokerage	547	24.3	5.6	112.2
Trading & Sales	268	122.9	18.1	373.2
All Losses Combined	3,222	66.2	8.0	424.9

Table 4.2. Descriptive Statistics and Correlations of Variables Used in Regressions

Mean, median, standard deviation, minimum and maximum values of explanatory variables used in regression models, 1973 to 2004 inclusive. Market Cap is the market capitalization of firms in the database, expressed in $US million. Scaled Loss is the logarithm of losses divided by market capitalization. Unemployment is the yearly U.S unemployment rate, expressed as a percentage. ΔGDP is the percentage change in yearly U.S. real GDP. Bankruptcies is the yearly number of U.S. personal bankruptcies, in thousands. Correlations are for yearly values of variables. Correlations significant at the one, five, and ten percent level and denoted ***, **, and *, respectively. PANEL A: Descriptive Statistics. PANEL B: Correlations.

PANEL A: Descriptive Statistics

Variable	Mean	Median	StdDev	Min	Max
Market Cap ($M)	6,410	1,050	15,220	3,650	147,120
Scaled Loss	−11.38	−11.23	2.65	−18.47	−1.23
Unemployment (%)	6.31	6.05	1.41	4.00	9.70
ΔGDP (%)	3.08	3.50	2.05	−1.94	7.19
Bankruptcies ($000)	857.9	812.9	462.8	284.5	1,625.2

PANEL B: Correlations

	Unemp	ΔGDP	Bankrupt
Scaled Loss	0.14***	−0.03	0.23***
Unemployment		−0.23	−0.70***
ΔGDP			0.04

Table 4.3. Descriptive Statistics of Losses From U.S. Financial Firms During Market Crises

Number of scaled losses and scaled fraudulent losses from U.S. financial firms during bad and good economic regimes, during business cycles, and during economic crises, including median scaled loss, and standard deviation, 1973 to 2004 inclusive. Scaled loss is the loss divided by firm market cap, where market cap is expressed in $US million. Low and High GDP growth refer to losses occurring during periods of low and high GDP growth, respectively. High and Low Unemployment refer to losses occurring during periods of high and low unemployment, respectively. NBER Recession and Expansion refer to losses occurring during NBER-dated recessions and expansions, respectively. The last column are p-values from Kruskal-Wallis test. PANEL A: All losses from U.S. financial firms. PANEL B: Fraudulent losses from U.S. financial firms.

PANEL A: U.S. Financial Losses Economic Regime	Number	Median	Std Dev	K-W test p-value
Low GDP Growth	362	18.6	2,204.0	
High GDP Growth	294	4.2	245.5	0.0001
High Unemployment	358	14.2	655.9	
Low Unemployment	298	7.3	2,346.0	0.0055
NBER Recession	49	9.6	1,187.2	
NBER Expansion	607	9.9	1,690.9	0.8619
All Losses	656	9.8	1.675.9	
PANEL B: U.S. Fraudulent Losses				
Low GDP Growth	123	44.3	2,688.8	
High GDP Growth	93	7.8	232.7	0.0001
High Unemployment	96	24.2	559.3	
Low Unemployment	120	14.7	2,701.3	0.2299
NBER Recession	18	15.8	387.6	
NBER Expansion	198	21.2	2,143.8	0.4662
All Fraudulent Losses	216	21.2	2,056.2	

Table 4.4. Regression of Yearly Scaled Losses on U.S. GDP and Unemployment

Model $Y_{it} = \alpha + \beta_X X_t + \beta_F Fin_i + \beta_{FX} Fin_i \times X_t + \varepsilon_{it}$ for losses experienced by U.S. firms, 1973 to 2004 inclusive. The dependent variable is the scaled loss, defined as the log of losses divided by firm market capitalization. Economic variables X_t are ΔGDP, the raw yearly change in U.S. real GDP, Unemp, the yearly U.S. rate of unemployment, and ΔPersBank, the yearly change in the proportion of personal bankruptcies (personal bankruptcies divided by personal bankruptcies plus business bankruptcies). Fin_i is a dummy variable taking on the value one if loss i results from a U.S. financial firm, and zero otherwise. $Fin_i \times X_t$ is an interaction between X_t and Fin_i. Lagged values of X_t are one-year lags. Coefficients marked with *, **, *** are significant at the ten percent, five percent, and one percent level, n is the sample size, R_a^2 is the adjusted coefficient of multiple determination, and t-statistics are in parentheses. There are 1,955 observations used in the regressions.

	Intercept α	Macro Variable β_X	Financial Dummy β_F	Financial $\times$Macro β_{FX}	R_a^2
ΔGDP	2.6^{***}	0.005	0.392	-0.273^{**}	0.01
	(13.9)	(0.7)	(1.2)	(−2.3)	
Lag ΔGDP	2.6^{***}	−0.027	0.312	-0.248^{**}	0.01
	(14.4)	(−0.4)	(1.0)	(−2.2)	
Unemp	1.1^{**}	0.286^{***}	-2.4^{***}	0.378^{***}	0.03
	(2.5)	(3.7)	(−3.2)	(2.8)	
Lag Unemp	0.42	0.404^{***}	-1.8^{**}	0.253^{**}	0.04
	(1.1)	(5.6)	(−2.6)	(2.1)	

Table 4.5. Regression of Yearly Scaled Losses on U.S. GDP, Unemployment, and Fraud

Model is $Y_{it} = \alpha + \beta_X X_t + \beta_F Fraud_{it} + \beta_{FX} Fraud_{it} \times X_t + \varepsilon_{it}$ for losses incurred over 1973 to 2004 inclusive and experienced by U.S. firms (Panel A) and by U.S. financial firms (Panel B). For Panel C, model is $Y_{it} = \alpha + \beta_X X_t + \beta_{IF} IF_{it} + \beta_{EF} EF_{it} + \beta_{IFX} IF_{it} \times X_t + \beta_{EFX} EF_{it} \times X_t + \varepsilon_{it}$ for U.S. financial firms. The dependent variable is the scaled loss, defined as the log of losses divided by firm market capitalization. Economic variables X_t are ΔGDP, the raw yearly change in U.S. real GDP, and Unemp, the yearly U.S. rate of unemployment. Lagged values of X_t are one-year lags $Fraud_{it}$ is a dummy variable taking on the value one if loss i in year t results from fraud, and zero otherwise, and $Fraud_{it} \times X_t$ is an interaction between X_t and $Fraud_{it}$. IF_{it} is a dummy variable taking on the value one if loss i in year t results from internal fraud, and EF_{it} a dummy variable for external fraud. $IF_{it} \times X_t$ and $EF_{it} \times X_t$ are interactions between X_t and internal and external fraud, respectively. Regression coefficients marked with *, **, *** are significant at the ten percent, five percent, and one percent level, n is the sample size, R_a^2 is the adjusted coefficient of multiple determination, and t-statistics are in parentheses.

	Intercept α	Macro Variable β_X	Fraud Dummy β_F	Fraud ×Macro β_{FX}	R_a^2
Panel A: All U.S. Firms, $n = 1,955$					
ΔGDP	2.5^{***}	−0.021	1.1^{**}	-0.379^{**}	0.01
	(15.3)	(−0.3)	(2.6)	(−2.4)	
LagΔGDP	2.6^{***}	−0.054	0.962^{**}	-0.321^{**}	0.01
	(16.1)	(−0.9)	(2.3)	(−2.1)	
Unemp	0.711^{*}	0.325^{***}	-2.3^{**}	0.439^{***}	0.02
	(1.9)	(4.7)	(−2.3)	(2.5)	
Lag Unemp	0.125	0.436^{***}	−1.3	0.241	0.02
	(0.4)	(6.8)	(−1.4)	(1.5)	
Panel B: U.S. Financial Firms, $n = 643$					
ΔGDP	2.4^{***}	−0.114	1.6^{***}	-0.406^{*}	0.02
	(6.4)	(−0.8)	(2.6)	(−1.7)	
LagΔGDP	2.5^{***}	−0.166	1.6^{***}	-0.402^{*}	0.02
	(7.6)	(−1.4)	(2.7)	(−1.8)	
Unemp	−0.565	0.484^{***}	−2.9	0.497^{*}	0.05
	(−0.7)	(3.3)	(−1.5)	(1.9)	
Lag Unemp	−0.926	0.551^{***}	−0.911	0.257	0.06
	(−1.3)	(4.2)	(−0.7)	(1.1)	

Table 4.5. Regression of Yearly Scaled Losses on U.S. GDP, Unemployment, and Fraud (Continued)

	Intercept α	Macro Var β_X	Int Fraud β_{IF}	Ext Fraud β_{EF}	IF× Macro β_{IFX}	EF× Macro β_{EFX}	R_a^2
Panel C: U.S. Financial Firms, $n = 643$							
ΔGDP	2.4***	−0.114	2.4***	1.0	−0.489	−0.385	0.03
	(6.4)	(−0.8)	(2.9)	(1.3)	(−1.5)	(−1.3)	
LagΔGDP	2.5***	−0.166	2.7***	0.820	−0.582*	−0.311	0.03
	(7.6)	(−1.3)	(3.3)	(1.1)	(−1.9)	(−1.6)	
Unemp	−0.694	0.505***	−2.2**	−1.8	0.614	0.329	0.06
	(−0.8)	(3.4)	(−1.2)	(−1.0)	(1.8)	(1.0)	
Lag Unemp	−1.0	0.561***	−0.767	−0.191	0.327	0.041	0.07
	(−1.4)	(4.3)	(−0.5)	(−0.1)	(1.1)	(0.1)	

Table 4.6. Regression of Yearly Scaled Losses on U.S. GDP and Unemployment, by Selected Business Line

Model is $Y_{it} = \alpha + \beta_X X_t + \varepsilon_{it}$ for losses experienced by U.S. financial firms, 1973 to 2004 inclusive. The dependent variable is the scaled loss, defined as the the log of losses divided by firm market capitalization. Economic variables X_t are ΔGDP, the raw yearly change in U.S. real GDP (Panel A), and Unemployment, the yearly U.S. rate of unemployment (Panel B). Lagged values of X_t are one-year lags. Regression coefficients marked with *, **, *** are significant at the ten percent, five percent, and one percent level, n is the sample size, R_a^2 is the adjusted coefficient of multiple determination, and t-statistics are in parentheses.

	ΔGDP			Unemployment		
	α	β_X	R_a^2	α	β_X	R_a^2
Asset Management						
Macro Variable $n = 36$	2.9***	−0.151	0.00	−3.6	1.1*	0.12
	(2.8)	(−0.4)		(−1.4)	(2.4)	
Lagged Variable $n = 36$	4.5***	−0.793*	0.07	−2.8	1.0**	0.11
	(4.0)	(−1.9)		(−1.2)	(2.3)	
Commercial Banking						
Macro Variable $n = 88$	5.1***	−0.969***	0.10	−1.1	0.667**	0.03
	(6.2)	(−3.3)		(−0.6)	(2.0)	
Lagged Variable $n = 88$	3.4***	−0.317	0.01	−0.624	0.562*	0.03
	(4.4)	(−1.1)		(−0.4)	(1.9)	
Retail Banking						
Macro Variable $n = 253$	3.5***	−0.481***	0.03	−1.2	0.634***	0.04
	(7.5)	(−2.7)		(−1.1)	(3.3)	
Lagged Variable $n = 253$	3.3***	−0.391**	0.02	−0.236	0.461***	0.03
	(7.1)	(−2.2)		(−0.2)	(2.7)	
Retail Brokerage						
Macro Variable $n = 63$	0.722	0.197	0.00	−7.0***	1.6***	0.22
	(0.6)	(0.5)		(−3.6)	(4.3)	
Lagged Variable $n = 253$	4.5***	−1.2***	0.16	−5.9	1.3	0.22
	(4.6)	(−3.5)		(−3.5)	(4.3)	
Trading & Sales						
Macro Variable $n = 27$	2.6*	0.08	0.00	5.9	−0.552	0.00
	(1.7)	(0.1)		(1.4)	(−0.8)	
Lagged Variable $n = 27$	1.2	0.832*	0.07	2.1	0.110	0.00
	(1.1)	(1.7)		(0.9)	(0.3)	

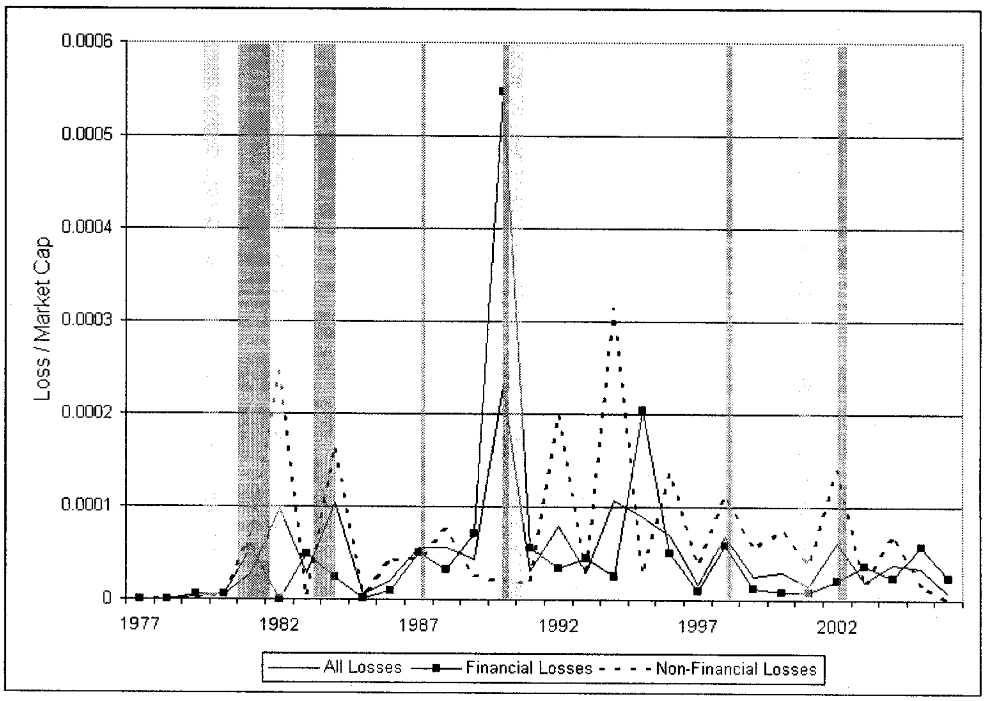
Table 4.7. Percentiles of Losses From Retail Banking Due to Internal Fraud, Under Changing Economic Conditions

Ninety-nine and 99.5 percentiles of losses due to internal fraud in the retail banking line of international banks, 1973 to 2004 inclusive. The percentiles are calculated from the histogram of losses (Empirical) and from the Pareto, Lognormal, and Inverse Gaussian distributions fitted to the loss data. Good and Bad refers to percentiles obtained from losses experienced during high and low periods of U.S. unemployment or periods of low GDP growth, while All refers to percentiles obtained from all the losses. The p-values in Panel A are from the Kruskal-Wallis test, those in the other panels are from the likelihood ratio test, where the restricted likelihood is that obtained using the small losses, but with parameters estimated using the large losses, and the unrestricted likelihood is that obtained using the small losses, and with parameters estimated using the small losses. All entries are in US$ million. PANEL A: Empirical percentiles. PANEL B: Percentiles from the Pareto distribution. PANEL C: Percentiles from the Lognormal distribution. PANEL D: Percentiles from the Inverse Gaussian distribution.

PANEL A: Empirical Percentiles							
		99%			99.5%		
	Good	Bad	All	Good	Bad	All	p-value
Unemployment	596	666	654	756	1,148	749	0.0462
ΔGDP	192	721	654	256	1,241	749	0.2026
PANEL B: Pareto Percentiles							
Unemployment	367	605	487	668	1,158	914	0.0487
ΔGDP	188	1008	487	294	2,175	914	0.0003
PANEL C: Lognormal Percentiles							
Unemployment	181	284	232	259	413	334	0.0110
ΔGDP	124	374	232	170	559	334	0.0001
PANEL D: Inverse Gaussian Percentiles							
Unemployment	374	585	483	520	829	678	0.0001
ΔGDP	165	806	483	216	1,182	678	0.0005

Figure 4.1. Average Yearly Losses From U.S. Financial and Non-Financial Firms, as a Proportion of Market Capitalization

Average yearly loss as a proportion of market capitalization, for losses incurred by U.S. financial and U.S. non-financial firms, 1977 to 2004 inclusive. Dark shaded regions are periods of bear markets, as defined by Ned Davis Research, Inc. Light shaded areas are periods of recessions, as defined by NBER.



CHAPTER 5
CONCLUSION

This thesis has examined issues related to hedge fund survival, incentives among CTA managers, and operational risk. With the long lock up period and infrequent redemption that hedge funds impose, investors are demanding funds likely to remain in operation for many years and avoid liquidation, so that the large capital losses that often follow liquidation can be avoided. The recent popularity of funds offering portfolio insurance and capital guarantees is testimonial to this new trend. Survival analysis can serve as a tool for due diligence of hedge funds, since it can help identify fund characteristics associated with longevity. Many studies of hedge fund survival and of survivorship bias are incomplete because they do not separate liquidation from the other exit types that hedge funds can experience. It is important to isolate liquidation and identify determinants of liquidation solely, since other exits have little economic consequences for investors. In this thesis we treat the different types of exits that hedge funds can experience separately, to provide estimates of survival and mortality that are more economically meaningful than those produced in previous studies. The results provide investors with a new method with which to evaluate and screen hedge funds, complementing studies on performance persistence, diversification, and asset pricing already at their disposal in the literature.

Commodity Trading Advisors (CTA) are a special class of hedge fund that trade in futures contracts, and that tend to be small. Previous research has shown that the negative relationship between size and returns can be explained by several factors, including increasing risk aversion with age, the desire to preserve an acquired reputation and other career concerns, and liquidity and price impact effects. In this thesis we show that the negative relationship observed among CTAs in previous research can also be explained by the two-tier fee structure charged by CTAs. Managers earning most of their compensation from incentive fees must chase high returns to reach their hurdle rate and trigger the incentive fee. In this quest they incur high volatility. As managers acquire more assets they earn an increasing amount of compensation from management fees. This allows them to rest on their laurels, and behave more like indexers and asset gatherers.

Because of low transparency and loose regulation, investors of hedge funds and CTAs are particularly exposed to operational risk. In this thesis we analyze operational losses from U.S. firms and international banks, and show how these losses are cyclical. In particular, we find that losses tend to increase during periods of high unemployment, but to decrease during periods of high GDP growth. We also find that GDP growth is linked to a reduction in fraud perpetrated on U.S. financial firms by insiders of the firm. GDP growth is not as strongly linked to external fraud, however. These results support our claim that when economic conditions deteriorate, individuals are likely to commit fraud, possibly because of the financial hardship that bad times precipitate.

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