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Estimating Operational Risk for Hedge Funds

The ω-Score

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Abstract

Using a complete set of the SEC filing information on hedge funds (Form ADV) and the TASS data, we develop a quantitative model called the ω-Score to measure hedge fund operational risk. The ω-Score is related to conflict of interest issues, concentrated ownership, and reduced leverage in the ADV data. With a statistical methodology, we further relate the ω-Score to readily available information such as fund performance, volatility, size, age, and fee structures. Finally, we demonstrate that this risk score can be used to effectively predict fund failures in the future.

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The hedge fund industry has experienced tremendous growth in the past decade. It is estimated that there are about 9,000 hedge funds worldwide with more than $1.8 trillion under management, compared with only $39 billion in 1990. In particular, institutional investors are increasingly involved in investing hedge funds. For example, as of May 2006, the Massachusetts Pension Reserves Investment Management, Harvard University, and MIT have invested $4.0 billion, $3.1 billion, and $2.0 billion in hedge funds, respectively.[2]

However, the hedge fund industry is also known for its high attrition rate. Selecting a successful manager could be very challenging. In a white Paper by Capco, the authors estimate that half of the failed funds are due to operational risk.[3] According to the International Association of Financial Engineers, operational risk is defined as "losses caused by problems with people, processes, technology, or external events."[4] More specifically, these include the risks of failure in the internal operational, control and accounting systems, failure of the compliance and internal audit systems and failure of employee fraud and misconduct. For example, losses due to misrepresentation (e.g., Sentinel Management Group, Wood River Capital Management, and International Management Associates) and failures due to management fraud (e.g., Bayou, Tradewinds International, Groundswell Capital, and KL Financial Group) can all be thought of as operational risk events.

The increasing demand for hedge funds together with potential failures due to operational risk impose a necessary operational due diligence process for selecting high quality managers, as commonly practiced by many prudent investors before their investments. In recent research, Brown, Fraser, and Liang (2007) argue that effective due diligence is a source for hedge funds alpha. They find that large funds of funds have the

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[2] Christine Williamson, "Investors say: Supersize it. More than 30 U.S. institutions invest $1 billion or more each", Pensions & Investment, May 1, 2006.
[3] See "Understanding and Mitigating Operational Risk in Hedge Fund Investments", a Capco White Paper, March, 2003.
[4] INTERNATIONAL ASSOCIATION OF FINANCIAL ENGINEERS, Report of the Operational Risk Committee: Evaluating Operational Risk Controls, CONCLUSIONS AND FINDINGS ON THE TOPIC OF: "How should firms determine the effectiveness of their operational risk controls?", November 2001, www.iafe.org.

capability of absorbing the fixed costs associated with due diligence. The AIMA has developed a comprehensive questionnaire for hedge fund due diligence with detailed questions ranging from management, strategy, risk, to service providers.[5] Due diligence performed by investing institutions is often conducted to the extent of a background check, an on-site office visit, manager interviews, automated legal alert systems on fund personnel activities, in addition to review of publicly available information. Although due diligence is intensively conducted in the hedge fund industry, the current practice is mostly focused at the qualitative level instead of the quantitative level. This is because assessing operational risk necessarily relies upon intangible variables such as historical manager behavior and human factors relating to unethical or illegal acts. However, as the number of funds increases, and the fixed cost of evaluating them remains constant, there is for a need for numerical scoring models in the spirit of Altman's *z*-Score model (1968) for bankruptcy. While a quantitative model can never fully replace human judgement, and the processing of "soft information" can help prioritize the due diligence process. Indeed, with the increasing flow of available information about managers, a reliable model is essential to reduce the dimensionality of the due-diligence process in order to better assess the operational risk exposure.

In this paper, starting from hedge fund filings with the SEC (Form ADV), we investigate the operational risk issue in depth for the industry. Form ADV is potentially relevant to the operational risk issue, as one of the purposes of hedge fund disclosure, according to the SEC is "keeping unfit persons from using hedge funds to perpetrate fraud."[6] Thus, the SEC devised a set of questions intended to uncover past violations by the investment adviser, and to elucidate condition that might leave clients vulnerable to future fraud or operational failure. Per the SEC requirement, major hedge funds based in the U.S. with more than 14 clients, assets of at least $25 million and a lockup period less than two years, as well as any internationally based fund with at least 14 U.S. based investors, filed Form ADV with the SEC by February 1, 2006. While some advisers chose not to comply with this regulation, anticipating a future challenge, the vast majority filed as per the SEC requirement. However, on June 23, 2006, the U.S. Court of Appeals

[5] See http://www.fortitudecapital.com/docs/dd/aima_questionnaire.pdf.
[6] See http://www.sec.gov/rules/final/ia-2333.htm

for the District of Columbia Circuit vacated the rule changes that had required many newly-registered hedge fund managers to register as investment advisers under the 1940 Investment Advisers Act. Since then, some hedge funds have started to deregister their filings. Because our ADV data was downloaded before June 2006, the data provides the only relatively complete database on hedge fund registration for studying operational risk.

In our analysis of these filings, we find that operational risk, as measured by past legal or regulatory problems incurred by investment advisers or fund managers, is strongly related to ADV variables such as conflict of interest, ownership, and leverage. Hence, it is possible to develop an instrument for assessment of operational risk based on the ADV data. Given that Form ADV filings are limited going forward and hence, complete information on operational risk co-factors may not be observable in the future, alternative models based on available information are warranted. In this article, we use variables in the Lipper-TASS database to develop this instrument. Through a statistical mapping technology, we are able to link the ADV variables with the TASS variables, then we use the Lipper-TASS variables to develop a risk instrument we call the ω-Score, which is a function of fund performance, volatility, fund age and size, and fee structure.

This paper is related to Brown, Goetzmann, Liang, and Schwarz (2007). In that work we used the ω-Score to explore the question of whether Form ADV information was redundant in the investment marketplace. In this paper we turn to the crucial question of whether the ω-Score can be used to predict fund failure in the future. The main contribution of this paper is a scoring model for detecting operational risk in the hedge fund industry. While we anticipate that more sophisticated models can be developed in the future, this paper demonstrates the feasibility of scoring funds according to their potential for operational risk events.

Data

We use data from two different sources. The first is the well known Lipper-TASS database. In order to capture the changes of fund characteristic data over time and back test our model we have nine different versions of the data covering the period from

1998-2006. We use the February, 2006 TASS data to match management companies with the SEC Form ADV filings. The February, 2006 TASS database contains 4,019 live hedge funds and 2,491 defunct hedge funds. It also includes the management company information. The second source of data is the Form ADV data from the SEC investment adviser website.[7] Each Form ADV contains information on an investment adviser. The filing consists of 12 items and at least three schedules.[8] Items 1 through 6 contain descriptive information on the firm, including its address, structure, number of employees in various positions and a breakdown of investor types. Items 7 and 8 look at potential conflicts of interest of the firm. Item 9 examines the custody of various assets while Item 10 looks at the control persons of the firm. Item 12 provides information to allow the SEC to examine the effect of the regulation on small businesses.

Item 11 is of particular interest to us as it identifies any "problems" that the management or related advisory affiliates have, including felonies, investment-related misdemeanors or any agency, SEC, CFTC, or self-regulatory issues. If the firm answers yes to any of the questions on Item 11, it must also file a Disclosure Reporting Page, which expands on the problem identified in Item 11. Schedule A includes the direct owners and executive officers of the firm, Schedule B lists the indirect owners of the firm and Schedule D includes a list of other business locations, other locations of records, previously non-listed control persons and a list of the limited partnerships in which the firm participates.

We downloaded Form ADV data directly from the SEC website.[9] To match Form ADV's to hedge fund companies, we implemented a two-phase search. First, we searched for the common management company listed for each fund.[10] If that search was unsuccessful, we then searched for any unique names that appeared in the fund's name. In a majority of cases, the company was identified using just the management company

[7] See http://www.adviserinfo.sec.gov/IAPD/Content/IapdMain/iapd_SiteMap.aspx, the SEC investment adviser website.
[8] There are additional forms if the company has a "problem" as defined later in the paper or if the company also filed with a state agency.
[9] Data were downloaded in March and April 2006. It is important to note the ADVs are dynamic in that the SEC will update the information on the investment adviser website as soon as new information is available. Thus, the data downloaded in the future will not match exactly the data used in this study.
[10] A few of the funds also listed an investment adviser with a different name than the management company. We also included these companies in our search if the management company was not located.

information.[11] Note that, since the requirement to register began on February 1, 2006, our searches only encompassed the live database. To insure matches, one fund listed in the TASS dataset had to be matched to a fund listed on Form ADV.[12]

Following the above procedure, we successfully identified 879 management companies out of 1,697 (or 51.8%) listed in TASS. These management companies represent 2,299 (57.2%) of the 4,019 live funds in the live TASS database. The unmatched TASS funds include funds with less than the $25 million in assets (22% of unmatched funds), funds with lockups longer than two years (2%), and foreign companies with fewer than 14 U.S. investors (73%).[13]

Empirical Results

Defining "Problem Funds" and "Non-Problem Funds". In order to assess operational risk, we need to define the term. We start by classifying funds as "problem" funds and "non-problem" funds in the ADV data.

Problem funds are those whose management companies answered yes to any of the questions on Item 11 in Form ADV while non-problem funds answered no to all questions on Item 11. Problems covered on Item 11 include any past felony or financial related misdemeanor changes or convictions. The form also includes questions concerning any SEC, CFTC, federal or state agency or other regulatory disciplinary action as well as civil lawsuits. Of the 2,299 funds in our sample, 368 (or 16%) have management firms that answered yes to at least one question on Item 11.[14] The percentage of funds with problems is not being driven by only a few management companies; of the 879 management companies, 126 companies, or 14.3%, answered yes to a question on Item 11.

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[11] We did not explicitly keep track of this breakdown, but estimate that fewer than 15% of all matches were made using the fund name.

[12] Some of the ADV filings did not list any funds. In these cases, the name and address of the ADV was used to verify a match.

[13] As of the beginning of April 2006, we were unable to match around 100 management companies in TASS with U.S. addresses and over $25 million in assets. There are a variety of reasons for these companies not to be registered, including a lockup period change, a reduction in assets or an error in the TASS database.

[14] These results were also run excluding fund-of-funds as their structure is different than hedge funds. There are no material differences between those results and the reported results.

Table 1: Performance Statistics and Fund/Manager Characteristics of "Problem" and "Non-Problem" Funds

	"Problem" Funds			"Non-Problem" Funds				
	N	Mean	Median	N	Mean	Median	Diff	*p*-value
Avg Return	310	0.77	0.68	1603	0.91	0.79	-0.14	0.00**
Std Dev	308	2.50	1.66	1568	2.71	2.02	-0.21	0.15
1st order Auto Corr	283	0.12	0.14	1441	0.12	0.13	0.00	0.60
Sharpe Ratio	308	0.28	0.25	1568	0.36	0.26	-0.08	0.01*
AUM ($mm)	334	217.32	59.18	1653	179.96	54.00	37.36	0.20
Age (Years)	367	5.60	4.50	1929	4.96	3.83	0.64	0.01**
Min Investment	367	0.96	0.50	1926	1.28	0.50	-0.32	0.33
Management Fee (%)	367	1.37	1.50	1929	1.38	1.50	-0.01	0.71
Incentive Fee (%)	367	15.25	20.00	1929	17.49	20.00	-2.24	0.00**
High Water Mark	367	0.69	1.00	1929	0.82	1.00	-0.13	0.00**
Lockup Period	367	4.00	0.00	1929	4.43	0.00	-0.43	0.21

NOTE: This table reports cross-sectional means, medians and the difference in means of descriptive statistics for both "Problem" and "Non-Problem" funds in our population of hedge funds filing Form ADV. "Problem" funds are any TASS fund whose management company answered "Yes" to any of the questions on Item 11 of Form ADV. "Non-Problem" funds are all other TASS funds that filed Form ADV. Panel A reports results for performance statistics. Avg Return, Std Dev, 1st Order Auto Corr, Sharpe Ratio are the average return of the fund, the standard deviation, the first order autocorrelation, Sharpe Ratio of the fund over its life.

Table 1 examines the performance differences and fund characteristics between problem and non-problem funds. There is no significant difference in terms of standard deviation or autocorrelation of returns. Problem funds are older than non-problem funds, indicating that it is more likely for a fund to encounter a problem over a longer time horizon. The mean return, Sharpe Ratio, incentive fee level, and the percentage of using high water mark are significantly lower for problem funds, indicating problem funds may have a lower institutional quality.

Defining Operational Risk. Legal and regulatory compliance issues provide a simple – and measurable – proxy for operational risk more broadly defined to include personnel problems, investment process, internal control, portfolio pricing, or compliance issues. On this basis we define legal and regulatory "problem funds" as those that have high operational risk while "non-problem funds" are those that have low operational risk. This definition is of course necessarily incomplete. Some of the legal and regulatory problems identified in the ADV forms may not be related to operational issues.

Furthermore, there may be funds with operational issues that have not yet attracted the attention of legal or regulatory authorities. Nevertheless, our analysis later in the paper shows that this definition is directly related to the current conflict of interest settings, ownership, and leverage ratios.

Operational Risk and the ADV Variables. Table 2 examines the relationship between conflict of interest variables and legal or regulatory problems. Panel A of Table 2 focuses on external relationships that represent potential conflicts of interest.[15] It reports the frequencies of positive answers to questions such as whether the manager has a related broker/dealer, investment company, investment adviser, commodities broker, bank, or insurance company. The frequency with which problem funds answered yes to these questions is universally higher than for non-problem funds. For example, while 73.9% of problem funds have a related Investment Adviser, only 41.6% of non-problem funds have the same issue. A similar dispersion exists for whether the firm has a related investment company—50.3% versus 15.8% for problem and non-problem funds, respectively. Note all the differences are significant at the 1% level.

Panel B focuses on internal potential conflicts of interest. The variable *AgencyCrossTrans* for example, asks whether a broker-dealer buys and sells broker clients' securities to advisory clients[16]. Only 2.3% of non-problem funds have this potential conflict of interest while over 30% of problem funds do. Problem vs. non-problem funds also differ significantly in the proportion of positive responses to the question of whether the firm recommends securities to clients in which a related party has some ownership interest (*RecSecYouOwn*),with 25% more problem funds exhibiting this conflict. As in Panel B, all of the differences between problem and non-problem funds are statistically significant at the 1% level. One particularly troubling statistic is that 84.8 percent of problem funds allow their personnel to buy and sell securities owned by the fund (*BuySellYourselfClients*).This is a rather direct conflict and is not acceptable

[15] There is a high correlation between all of the conflict of interest variables.
[16] These and later terms refer to checkboxes on Form ADV. For complete definitions of these terms and explanations see the SEC website http://www.sec.gov/about/forms/formadv.pdf

behavior in any public funds.[17] Both Panels A and B illustrate a strong relationship between legal and regulatory problems and various measures of internal and external conflicts of interest. O*therResearch* for example is a conflict variable in that it represents services obtained from a broker-dealer that the fund uses for its transactions. It is strongly significant. It suggests that the potential for conflicts of interest can lead to operational risk events, as measured by legal and regulatory problems.[18] This may be due to an higher incidence of fraudulent activity by managers of problem funds, or alternatively, it may be due to the fact that the simple presence of apparent conflicts of interest attracts more regulatory scrutiny and litigation. Again, all the differences are significant at the 1% level.

Panel C examines the ownership and capital structure differences between the two groups. Problem funds have a higher number of direct and controlling owners.[19] Interestingly, the number of direct owners in the form of non-individual domestic entities (*DirectDomestic*) is higher for problem funds than it is for non-problem funds. This implies that problem firms are more likely to be structured as a venture or partnership with another institution. It also has the effect of allowing owners to hide their names from the ownership list, although it does not exempt them from reporting. Finally, the *75% ownership* variable, which is the percentage of owners who own 75% of the company, is larger for problem funds. Theoretical results suggest that fear of expropriation—one source of operational risk—will make the management more concentrated rather than less concentrated. These results are confirmed in our data and all the differences are highly significant.

An important insight revealed in Panel C is the fact that problem funds are less able to raise leverage than non-problem funds. This issue is examined in depth in, Brown, Goetzmann, Liang, and Schwarz (2007) who argue that operational risk issues make prime brokers and lenders less willing to provide leverage and to provide less leverage.

[17] It is also striking that 69.3 percent of non problem funds also allow their personnel to trade fund securities on their own account. While significantly lower than the problem funds, it suggests that some of the "non problem" funds are "problem funds" in waiting.
[18] It is important to note that many jurisdictions prevent public funds engaging in soft dollar transactions because of this appearance of conflict.
[19] The definition of a controlling owner is set by the SEC. This is not a flag set by the company itself.

While financial risk is often associated with a high degree of leverage, it seems that the inability to raise leverage capital is itself a signal of serious operational issues uncovered in the due diligence conducted by potential lenders.

Given that an affirmative answer on Item 11 could reflect anything from involvement in a civil suit to conviction of a felony, it is useful to examine whether the type of offense makes a difference. Are the differences between problem and non-problem funds driven by one specific type of violation? To address this question, we classify the responses on Item 11 into four sub-groups. Group 1 includes managers who have been charged or convicted of a felony or a finance-related misdemeanor. Group 2 includes managers who have had their rights to trade revoked at some time in the past. Group 3 includes managers with some form of regulatory violation, including a falsification or fabrication. Group 4 includes managers involved in a civil suit. These classifications are non-exclusionary; one manager may show up in all four categories. For the sake of brevity, the results of this analysis are not presented, however they clearly indicate that the differences between problem and non-problem funds are not driven by a single category of violation.

Table 2: Operational Risk and the ADV Variables

Panel A: External Conflicting Relationships

With:	"Problem" Funds N	% Yes	"Non-Problem" N	% Yes	Diff	*p*-
Broker/Dealer	368	73.1	1929	23.7	49.4	0.00**
Investment Comp	368	50.3	1929	15.8	34.5	0.00**
Investment Adviser	368	73.9	1929	41.6	32.3	0.00**
Commodities Broker	368	53.5	1929	20.7	32.8	0.00**
Bank	368	40.5	1929	9.8	30.7	0.00**
Insurance	368	39.9	1929	8.3	31.6	0.00**
Sponsor of LLP	368	56.8	1929	21.5	35.3	0.00**

Panel B: Internal Conflicts

	"Problem" Funds N	% Yes	"Non-Problem" N	% Yes	Diff	*p*-
BuySellYourOwn	368	30.7	1929	8.3	22.4	0.00**
BuySellYourselfClie	368	84.8	1929	69.3	15.5	0.00**
RecSecYouOwn	368	75.5	1929	50.4	25.1	0.00**
AgencyCrossTrans	368	30.7	1929	2.3	28.4	0.00**
RecUnderwriter	368	69.0	1929	47.0	22.0	0.00**
RecSalesInterest	368	22.6	1929	15.7	6.9	0.00**
RecBrokers	368	46.7	1929	38.0	8.7	0.00**
OtherResearch	368	81.0	1929	70.5	10.5	0.00**

Panel C: Ownership/Capital Structure

	"Problem" Funds N	Mean	Median	"Non-Problem" Funds N	Mean	Median	Diff	*p*-value
Direct Owners	368	9.96	9.00	1929	7.33	6.00	2.63	0.00**
Controlling	368	8.28	7.00	1929	5.97	5.00	2.31	0.00**
75% ownership	366	0.73	1.00	1929	0.50	0.50	0.23	0.00**
Domestic Direct Corp	368	0.80	1.00	1929	0.49	0.00	0.31	0.00**
Indirect Owners	368	2.33	1.00	1929	1.37	0.00	0.96	0.00**
Leveraged	367	0.51	1.00	1929	0.57	1.00	-0.06	0.03*
Margin	280	0.35	0.00	1451	0.49	0.00	-0.14	0.00**
Personal Capital	109	1.26	0.00	622	2.62	0.00	-1.36	0.02*

NOTE: Panel A reports results for external conflicts of interest, while Panel B breaks down internal conflict data. *Broker/Dealer* is 1 if the fund has a related broker/dealer. *Investment Comp* is 1 if the fund has a related investment company. *Investment Adviser, Commodities Broker, Bank, Insurance* and *Sponsor of LLP* are 1 if the fund is related to one of these companies respectively. *BuySellYourOwn* is 1 if the company buys and sells between itself and clients. *BuySellYourselfClients* is 1 if a related party buys and sells securities also recommended to the fund. *RecSecYouOwn* is 1 if the fund recommends securities in which a related party has an ownership interest. *AgencyCrossTrans* is 1 if the fund performs agency cross transactions. *RecUnderwriter* is 1 if a related party recommends securities to clients for which they are the underwriter. *RecSalesInterest* is 1 if a related party recommends securities with a sales interest. *OtherResearch* is 1 if the fund uses external research. Panels C looks at fund/manager characteristics and governance/ownership variables, respectively. *High Water Mark, Leveraged* and *Margin* are 1 if the fund has a high water mark, uses leverage or uses margin. *Direct Owners* represents the number of direct owners. *Controlling* is the number of controlling owners. *75% ownership* is the percentage of owners who own at least 75% of the fund. *Domestic Direct Corp* gives the number of domestic corporations listed as direct owners. *Indirect Owners* represents the number of indirect owners.
**, * Significant at 1 and 5 percent respectively

Estimating an Operational Risk Measure. The above analysis shows the potential to construct quantitative proxies for operational risk. Funds with more conflict of interest issues, concentrated ownership, and low leverage ratios tend to have higher past operational risk, suggesting that such risks may also extend to future behavior. The challenge for the analyst is how to construct a quantitative proxy for funds that did not file such forms. In this paper, we describe a way to use more widely accessible data to construct operational risk scores.

We use the ADV results to build an observable proxy for operational risk based on the widely available Lipper-TASS data. We use canonical correlation analysis, a statistical tool, to construct an instrument. The instrument weights observable TASS variables, such as size, age and fee structure in such a way that the resulting variable is maximally correlated to a variable similarly constructed from weighted set of the potentially unobserved ADV variables like conflicts of interest and ownership structure. This weighting structure has the additional advantage of being computable for time periods earlier and later than 2006.[20]

The canonical correlation analysis proceeds as follows. We first identify TASS variables that prior research has shown to be associated with the probability of fund

[20] This canonical correlation procedure was first proposed by Hotelling (1936). A good textbook treatment can be found in Press (1972). For another finance application, see Brown et al. (2002).

failure. We then estimate a linear combination of these variables that maximally correlate with a similarly maximally correlated linear combination of the cross-section of Form ADV disclosures in February 2006 that match the TASS sample. This linear combination using the TASS variables is our univariate proxy for operational risk, or ω-Score.[21] Finally, we use this linear combination to proxy for unobserved Form ADV information in the years prior to February 2006 using a time-series of TASS fund characteristics.

Table 3: Canonical Correlation Analysis of TASS and ADV Data

TASS Variables		ADV Variables	
Previous Returns	-0.27**	AgencyCrossTrans	0.06*
Previous Std. Dev.	-0.35**	RelBrokerDealer	0.28**
Fund Age	-0.07**	RelInvestComp	0.24**
Log of Assets	0.13**	RelInvAdviser	0.24**
Reports Assets	0.12**	RelCommod	0.44**
Incentive Fee	-0.88**	RelBank	0.38**
Margin	-0.29**	RelInsur	0.44**
Audited	-0.19**	RelPartSponser	0.30**
Personal Capital	-0.29**	BuySellYourOwn	0.08*
Onshore	-0.05**	BuySellYourselfClient	-0.08**
Open to Inv.	0.08	RecSecYouOwn	0.33**
Accepts Managed	-0.13**	RecUnderwriter	0.26**
		RecSalesInterest	0.28**
		RecBrokers	-0.33**
		OtherResearch	-0.70**
Correlation Between		75% ownership	0.15**
TASS and ADV Panels	0.42**	DirectDomestic	0.31**

NOTE: This table reports the results of a canonical analysis relating operational risk ADV data to the observable TASS data. Panel A reported the results of the canonical analysis using 2,279 matched funds used to construct a univariate measure of operational risk, or ω-Score, using the linear combination implied by the TASS canonical variate. In Panel B we report regression results regressing annual fund return from 1994 to 2005 on the ω-Score updated each year using information in that year's TASS database on the basis of nine successive annual TASS datasets. *Previous Returns* are the average monthly returns from the previous year and *Previous Std. Dev.* is the monthly standard deviation from the previous year. *Age* and *Size* are the values from the end of the previous period. Other characteristic data are from the same period as the analysis. *Reports Assets* is a binary variable with a value of one if the fund reports assets and zero if it does not. Unreported style dummies and market betas were included in Panel B. The average number of observations is the average number of funds included in each year's cross section regression of fund returns against operational risk characteristic and style. Panel C shows the extent to which this measure of operational risk predicts leverage. The dependent variable in each regression is the average leverage of each fund as reported by TASS. The independent variable is that year's operational risk ω-Score. Unreported style dummies, as defined by TASS, and style dummies using the Brown-Goetzmann style classification procedure are included to control for style differences.

[21] Altman (1968) creates a related z-Score model to study credit scoring.

Table 3 reports the results of the canonical correlation analysis. Average monthly returns from the previous year, monthly standard deviation from the previous year, size at the beginning of the period, fund age and whether or not the fund reports assets are included in the analysis, as they have been previously related to fund death (Liang, 2000; Brown, Goetzmann & Park, 2001). The reported asset variable is a dummy variable with a value of one if the fund reports assets and zero if it does not. Other characteristic data from TASS, which relate to fund quality, are also included.

The maximal correlation between a linear combination of the TASS variables and a linear combination of Form ADV variables is 0.42 and is significant at the one percent level. The Form ADV variable loadings are almost all positively correlated with the canonical variable, indicating that a higher value has more operational risk. For example, a higher percentage of conflict of interest issues and higher ownership is related to higher operational risk. Higher return, standard deviation and incentive fee are all negatively correlated with the TASS canonical variable, indicating these are negatively related to operational risk.

Backtest: From 1994 to 2005, we compute the ω-Score each year using the raw coefficients from our original analysis on the matched sample.[22] We then regress fund returns on this operational risk ω-Score and include unreported style dummies to control for style differences.[23] We also control for market risk by estimating market betas for all funds each year and include the unreported betas in the yearly cross-sectional regressions. We use Brown and Goetzmann (2003) cluster-based style dummies. We begin in 1994 as TASS began keeping defunct funds in their dataset that year. Table 4 reports the results of this analysis.

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[22] Instead of assuming the TASS characteristic data were static over time, we utilize nine different TASS datasets over a period of nine years (1998-2006) to use the most accurate characteristic data related to each fund at each time period. We use returns from the most recent TASS dataset however, as they are the most complete and accurate. To control for backfill bias, we remove the first 18 months of returns for each fund. Since we don't have the fund characteristic data from 1994-1997, we used 1998 for calculating the scores for these years.

[23]Alternative specifications of the canonical analysis were performed, including adjusted returns. These alternative specifications did not change the relationship between operational risk and returns.

Table 4: Operational Risk Measure Predicting Returns

	B-G Style Dummies	
Year	coefficient	*t*-value
1994	-2.28%	-2.20*
1995	0.10%	0.12
1996	-3.27%	-4.76**
1997	-2.61%	-3.71**
1998	0.42%	0.60
1999	-0.13%	-0.14
2000	-0.18%	-0.25
2001	-0.42%	-0.95
2002	-1.48%	-4.43**
2003	-0.41%	-1.12
2004	-0.67%	-2.45*
2005	-0.11%	-1.31
Average Value	-0.92%	-2.66*
Average. Adjusted R-squared	40.17%	
Average Number of	1,027	

**, * Significant at 1 and 5%, respectively

Over the entire twelve-year history, we observe a negative ω-Score coefficient. The ω-Score is significant at the 5% level. Hence, operational risk is negatively related to fund returns. Of the twelve years, the operational risk variable is negatively related to returns in ten years. Note 1998 was an extremely difficult year for hedge funds due to the Russian debt crisis and the near collapse of the LTCM. 1998 is also a year of great attrition of hedge funds, which would eliminate *ex-post* some of the riskiest funds in the sample—a selection bias that is known to induce a spurious *ex-post* cross-sectional relationship between risk and return (see (Fung and Hsieh (2002, 2000), and Liang (2000)).

Using the ω-Score Out-of-Sample to Predict Hedge Fund Failures. Our previous results indicate that the ω-Score performed reasonably well in-sample at differentiating relative performance. Next, we want to see if this score predicts out-of-sample fund failure. We use the Cox Proportional Hazards model (1972) to predict the time to failure or survival time for a fund. The Cox Proportional Hazards model is the simplest and most common model used to model time to failure. It is most often used in a medical context to predict time to death given a certain medical treatment.

The core of this survival analysis is to model the hazard rate, $\lambda_i(t)$. $\lambda_i(t)$ specifies the instantaneous rate of failure of fund *i* at time *T*=*t*, conditional upon the fund's survival up to time *t*. More specifically, it is defined as follows:

$$\lambda_i(t) = \lim_{\Delta t \to 0^+} \frac{P(t \le T < t + \Delta t \mid T \ge t)}{\Delta t} \qquad (1)$$

In the Cox model, a vector of fund characteristics is introduced to explain the hazard rate. The components of this vector are called "covariates".

$$\lambda_i(t; z_i) = \lambda_0(t) e^{z_i^T \beta} \qquad (2)$$

where z^T denotes the transpose of the vector z and $\lambda_0(t)$ is the base-line hazard rate. The vector β is a set of the regression coefficients and assumed to be the same for all funds. To estimate Cox (1972, 1975) introduced the partial likelihood function, which eliminates the unknown baseline hazard $\lambda_0(t)$ and accounts for censored survival times.[24]

Brown, Goetzmann and Park (2001) use the Cox model to analyze hedge fund failure. They find that performance, risk and fund age play important roles in the fund termination. They use standard deviation as the risk measure. The higher the standard deviation, the higher the hazard rate of a fund.

In our paper, we are interested in the prognosis of the survival of the fund (as measured by the time to liquidation) based on the fund's ω-Score and its current age. On the basis of the June 2007 TASS database and the computed ω-Score, the regression results from the Cox Proportional Hazard model are as the following:

[24] See Kalbfleisch and Prentice (2002) for details.

Table 5: Regression results based on the Cox Proportional Hazards model

	N	ω-Score	*Chi-sq*		age	*Chi-sq*	
Convertible	491	0.04685	0.30		-0.00036	-0.15	
Dedicated Short	85	0.80538	2.73	**	0.00583	1.34	
Emerging Markets	778	0.33043	4.23	**	-0.00513	-2.07	*
Equity Market	649	-0.07736	-0.99		-0.00690	-3.23	**
Event Driven	1196	0.16691	1.76		-0.00739	-4.79	**
Fixed Income	493	0.36735	2.36	*	-0.01668	-4.03	**
Fund of Funds	2281	0.08577	1.36		-0.00729	-5.45	**
Global Macro	506	0.16105	1.45		-0.00440	-1.75	
Long/short Equity	3936	0.16229	3.33	**	-0.00746	-7.86	**
Managed Futures	1046	0.19395	2.77	**	-0.00803	-6.66	**
All (ex FOF)	9180	0.17825	6.39	**	-0.00672	-11.91	**

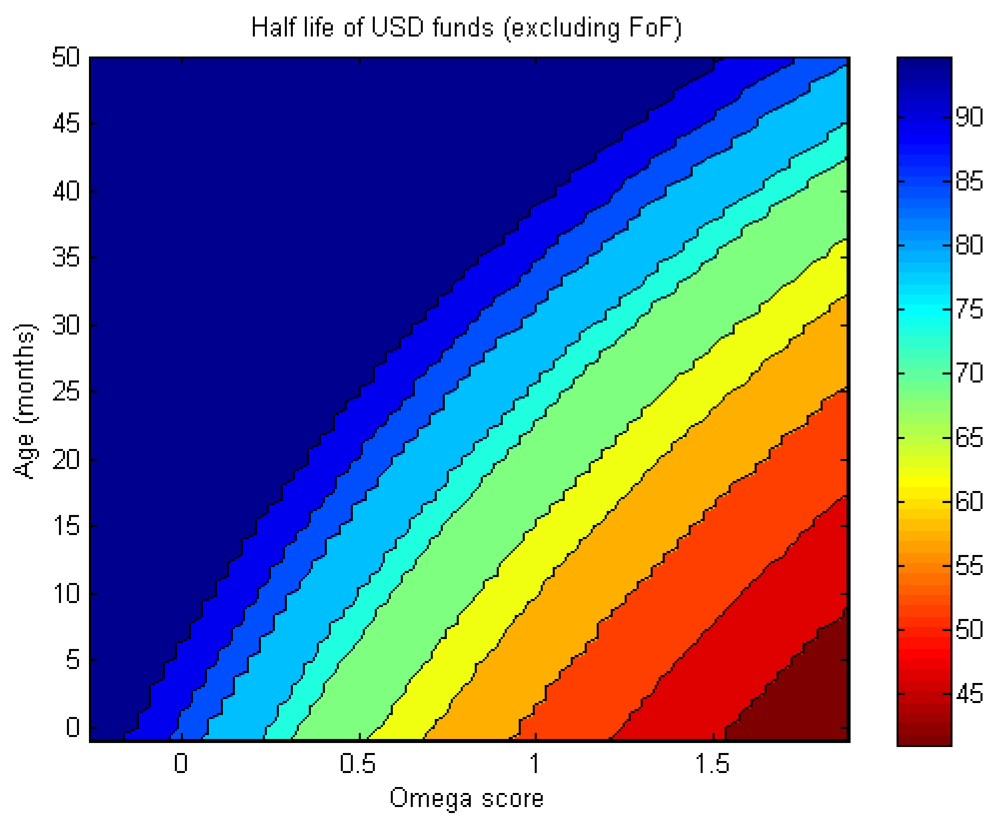
NOTE: The ω-Score is calculated from 1999 and onwards.

In this table, the coefficients give the increased risk of failure for a given unit increase in the ω-Score or age. The problem with this analysis is that the hedge fund industry is immature and many young funds have not died yet. This problem is referred to as "right censoring" and is accounted for in the analysis.

We see that the risk of failure significantly increases with the ω-Score and decreases with fund age across the TASS funds through the time period of our analysis. For all funds excluding fund of funds, both the ω-Score and fund age are significant at the 1% level.

Across all investment styles, the effect is reasonably similar across style categories. The ω-Score is significant for styles like dedicated short bias, emerging markets, fixed income securities, long/short equity, and managed futures, implying that operational risk is important to explain fund failures in these categories. However, the coefficients are insignificant for styles such as convertible arbitrage, equity market neutral, event driven, fund of funds, and global macro. For these styles, financial risk or other types of risk may be important co-factors of failure in these funds. For example, for fund of funds, the operational risk is minimized after all the necessary due diligence process has been performed by fund of fund managers; hence operational risk is not the major source for the failure of funds of funds. One of the interesting features of the analysis is that one can compute a projected half life based on the current age and ω-Score. Since *a priori* we have no clear theory which explains the time series behavior of the hazard rate or the interaction between age and ω-Score, we considered the results for the entire sample allowing for both strategy and year dummies, as well as all possible ω-Score interactions. Across all funds, the higher the ω-Score the smaller the half life of the fund, as indicated by Figure 1.[25]

Figure 1: Projected half life based on ω-Score and fund age



The ω-Score scale on the X axis corresponds to the 95% confidence interval from the empirical distribution of this quantity. The dark red zone, associated with young age and high ω-Score is where one does not want to be, as the fund half life is less than six years. Effectively, a high ω-Score (high operational risk) predicts a shorter fund life in the future.

[25] The half life may be overestimated given some of the funds have not been failed yet.

Conclusion

In this paper, we build an operational risk measure, the ω-Score, for hedge funds. This ω-Score is related to the SEC filing information (Form ADV) such as the conflict of interest issues, leverage, and ownership. Contrary to the conventional wisdom, a lower leverage is corresponding to higher operational risk as it reflects that low quality managers may not be able to attract enough outside funding. Further, we correlate the ADV variables with the readily available TASS variables in order to build an observable proxy for operational risk. The final ω-Score based on the TASS data is able predict fund failure effectively. The higher the ω-Score, the shorter is the projected fund life.

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