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 while operational risk is more significant than financial risk in explaining fund failure, there is a significant and positive interaction between operational risk and financial risk. This is consistent with rogue trading anecdotes that suggest that fund failure associated with excessive risk taking occurs when operational controls and oversight are weak.

May, 2008

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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 fund failures 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 fund alpha. They find that large funds of funds have the capability of absorbing the fixed costs associated with due diligence. The AIMA has

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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.

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 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, 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 potential for a quantitative approach to the operational risk issue. Form ADV is potentially relevant to operational risk, 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 for the District of Columbia Circuit vacated the rule changes that had required

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

many newly-registered hedge fund managers to register as investment advisers under the 1940 Investment Advisers Act. Since then, some hedge funds have deregistered 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 future fund failure. The main contribution of this paper is a scoring model for detecting operational risk in the hedge fund industry. We also examine the interaction between operational risk and financial risk, especially the marginal contribution of operational risk in predicting fund failure after controlling for financial risk. 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 backtest 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 management company information. The second source of data is the set of Form ADV filings 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.

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[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.

In a majority of cases, the company was identified using just the management company 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 this 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 in the affirmative 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[14]. Of the 2,299 funds in our sample, 368 (or

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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] 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 category of problem makes a difference. These classifications are non-exclusionary; one manager may show up in all four categories. One would expect that managers convicted of a felony would be treated differently in the market than those with less serious regulatory infractions. Many managers are involved in civil suits that are unrelated to operational concerns. Empirical analysis (not reported here) finds that felonies are treated with slightly greater severity than other

16%) have management firms that answered yes to at least one question on Item 11.[15] 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.

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. 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 using a high water mark are all significantly lower for problem funds, perhaps indicating problem funds may be of lower quality.

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issues. However, the same analysis reveals that any issue that requires an Item 11 response appears to be regarded as raising concerns on operational issues.

[15] 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.

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.[16] 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[17]. 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

[16] There is a high correlation between all of the conflict of interest variables.
[17] 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

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 behavior in any public funds.[18] 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.[19] This may be due to a 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.[20] 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.

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[18] 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.

[19] It is important to note that many jurisdictions prevent public funds engaging in soft dollar transactions because of this appearance of conflict.

[20] The definition of a controlling owner is set by the SEC. This is not a flag set by the company itself.

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 when they do, they evidently provide less leverage. 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.

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**
BuySellYourselfClients	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 ($mm)	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 a quantitative proxy for operational risk. Funds with more conflict of interest issues, concentrated ownership, and lower 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.[21]

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

[21] 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.[22] 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. The results of the canonical analysis using 2,279 matched funds were used to construct a univariate measure of operational risk, or ω-Score, using the linear combination implied by the TASS canonical variate. *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.

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

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

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.[23] We then regress fund returns on this operational risk ω-Score and include unreported style dummies to control for style differences.[24] 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.

[23] Instead of assuming the TASS characteristic data are 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. In this analysis we take as given the coefficient values determined on the basis of the relationship between TASS and ADV data given in Table 3. According to Congressional testimony before the House Financial Services Committee in March 13, 2007 a large majority of funds continue to register and file Form ADV. As this information becomes available, it should be possible to update the relationship and determine more precise measures of the ω-Score.

[24] 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 Observations	1,027	

NOTE: 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. **, * 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 of the years. Note that 1998 was an extremely difficult year for hedge funds due to the Russian debt crisis and the near collapse of the LTCM.[25] 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 (2000, 2002), 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-

[25] An alternative explanation is the important interaction with financial risk during the internet bubble. We thank the referee for this point.

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:

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

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

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

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.[26]

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[27]) based on the fund's ω-Score and a measure of

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

[27] Funds can leave the TASS database for many reasons. Funds closed to new investment may see no particular reason to report results into TASS, and many funds report in only on a quarterly basis leading to the appearance of fund failure in the last three months of the database. We define fund failure as funds which no longer report to TASS giving as their reason "Fund liquidated". The results reported in Table 5 use failures reported up to the end of July 2007 to avoid the possibility that the results are an artifact of the particular problems in August 2007 that afflicted many quant funds; extending the analysis to consider

financial risk. On the basis of the record of fund liquidations reported in the TASS database and the computed ω-Score, the regression results from the Cox Proportional Hazard model are given in Table 5. In this table, the coefficients give the increased risk of failure for a given unit increase in the ω-Score, financial risk (measured by $ln(\sigma)$ using data up to the date the ω-Score is computed), and the interaction between operational risk (ω-Score) and financial risk ($ln(\sigma)$)[28].

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

	N	ω	*t-value*	$ln(\sigma)$	*t-value*	$\omega \times ln(\sigma)$	*t-value*
Convertible Arbitrage	491	2.474	3.15**	0.279	2.02*	0.713	2.96**
Dedicated Short Bias	85	3.809	2.20*	-0.003	-0.01	0.912	1.85
Emerging Markets	778	1.382	3.85**	0.224	1.90*	0.342	3.11**
Equity Market Neutral	649	1.514	4.34**	0.338	3.15**	0.442	4.60**
Event Driven	1196	-0.037	-0.08	-0.065	-0.67	-0.069	-0.44
Fixed Income Arbitrage	493	0.550	0.58	-0.122	-0.61	0.059	0.20
Fund of Funds	2281	1.021	3.58**	-0.475	-3.74**	0.277	3.27**
Global Macro	506	0.334	0.55	-0.027	-0.18	0.059	0.34
Long/short Equity	3936	0.446	1.98*	-0.121	-2.28*	0.098	1.45
Managed Futures	1046	-0.791	-1.73	-0.123	-1.09	-0.304	-2.09*
All (ex FOF)	9180	0.704	5.27**	0.004	0.13	0.170	4.23**

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

Much of the discussion of major rogue trader risk events from Barings to Société Générale observe that significant financial risk was undertaken in an environment of poor operational controls[29]. We would therefore expect to find that high financial risk is associated with significant operational risk. If our measure of operational risk were merely proxying for financial risk we would expect operational risk to be wiped out in these regressions. The opposite is true. While operational risk is more significant than financial risk, there is a significant positive interaction which suggests that funds with

funds failing up to the end of March 2008 did not substantively change any of the results reported in Table 5.

[28]Since the hedge fund industry is relatively new there are many new funds that have not failed (yet). This is a well-known issue in duration analysis and is referred to in the literature as the "right censoring problem". A Heckman-like correction is standard to deal with this problem and was used in the results reported in Table 5.

[29] A particularly well-documented case of management failures associated with excess financial risk is given by the rogue trading losses at National Australia Bank (APRA 2004, PwC 2004).

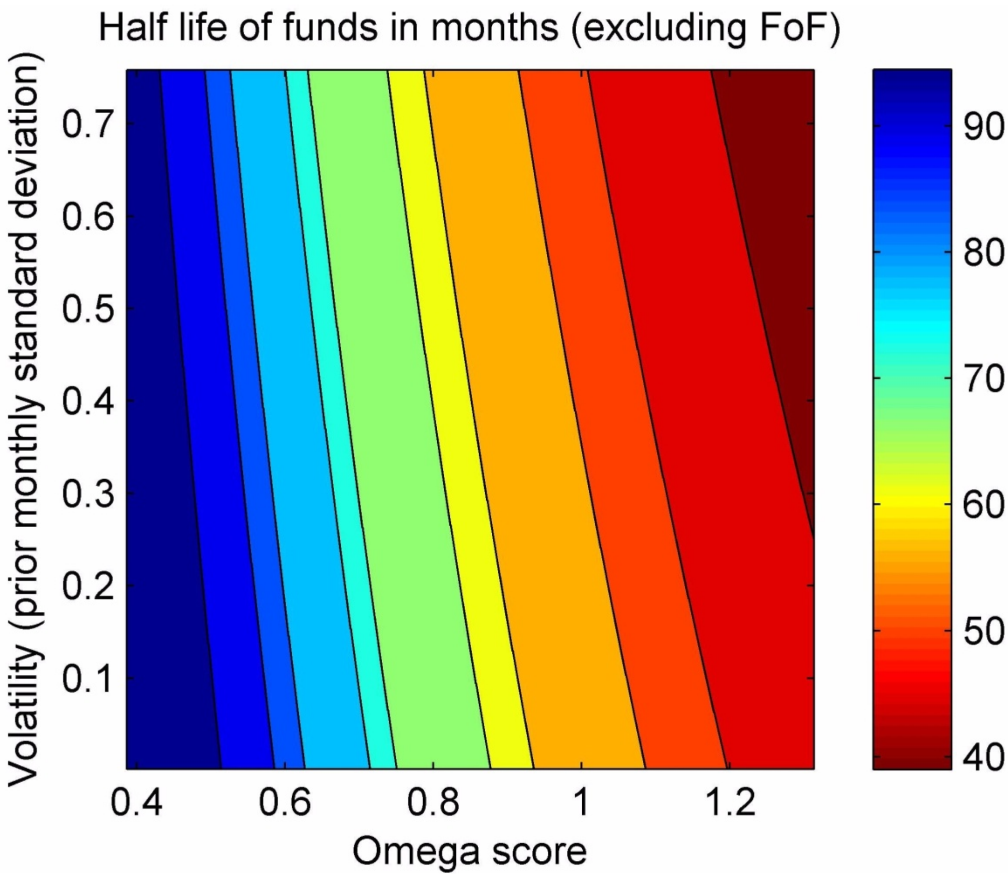
high degrees of operational risk are more subject to failure from financial risk, which is consistent with rogue trading anecdotes that suggest that fund failure associated with excessive risk taking occur when operational controls and oversight are weak.

The importance of operational risk is reasonably similar across style categories. The ω-Score is significant for styles like convertible arbitrage, dedicated short bias, emerging markets, equity market neutral, fund of funds, and long/short equity, implying that operational risk is important to explain fund failures in these categories. However, the coefficients are insignificant for styles such as event driven, fixed income arbitrage, global macro, and managed futures. For these styles, financial risk or other types of risk may be important co-factors of failure in these funds. For styles like convertible arbitrage, emerging market, event driven, fund of funds, and managed futures, higher operational risk is also related to higher financial risk.

Figure 1 depicts the half life of funds as a function of both operational and financial risk. Operational risk is clearly the most important factor determining half life of funds, while financial risk tends to magnify the deleterious effects of excess operational risk. It appears that while financial risk is an important factor in explaining fund failure, it is most pronounced when operational risk is high.[30]

[30] Liang and Park (2008) study the impact of performance, risk, asset size, fund age, leverage, and fund style in predicting fund failures.

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



The ω-Score scale on the X axis corresponds to the 95% confidence interval from the empirical distribution of this quantity. The Figure shows that half of all hedge funds with an ω-Score greater than one are dead within little more than fifty months. This projected lifespan falls as the ω-Score rises and the fall becomes most pronounced for funds with extreme financial risk. The dark red zone, associated with high volatility and high ω-Score is a region in which the investor does not want to linger, as funds in this category have a half life of less than three and a half years. Evidently, a high ω-Score (high operational risk), particularly when combined with high financial risk, leads to an extremely guarded prognosis for the continued life of the fund.[31]

[31] The duration analysis was implemented using MATLAB. It is readily available on most standard statistical software platforms such as SAS and other mainstream packages.

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, lower leverage corresponds to higher operational risk, suggesting that the capital marketplace may perceive these managers as operationally risky and rationally reduce their access to debt. 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 to effectively predict the future disappearance of funds from the sample. The higher the ω-Score, the shorter is the projected fund life.. Operational risk is of course not the only factor explaining fund failure. We find that there is a significant positive interaction with financial risk which suggests that funds with high degrees of operational risk are more subject to failure from excessive financial risk. This is consistent with rogue trading anecdotes that suggest that fund failure associated with excessive risk taking occur when operational controls and oversight are weak.

Our results are based on a snapshot at a point of time when most U.S. domiciled hedge funds were required to register with the Securities and Exchange Commission as investment advisors and file Form ADV. Our analysis shows that information contained on this form does indeed provide information relevant to a determination of operational risk. According to Congressional testimony before the House Financial Services Committee in March 13, 2007 a large majority of funds find it in their interest to register and file Form ADV even though there is no legal requirement for them to do so. Our analysis seems to show that there is an argument to be made in favor of more disclosure rather than less disclosure.

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