# Trust and Delegation

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This paper studies operational risk in the hedge fund industry using due diligence reports. Many funds suffer from operational problems, including limited disclosure of legal and regulatory issues. We use direct evidence of inadequate or failed internal processes to derive a canonical correlation-based measure for operational risk consistent with the Basel definition. It controls for selection bias using an extension of Heckman's (1979) procedure. Operational risk increases the likelihood of subsequent poor performance and fund disappearance, but does not influence investors' return-chasing behavior. Our study emphasizes the importance of information verification in the context of financial intermediation.

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> *The positive proposition that increasing the integrity of a firm will contribute to increasing its value is no different in kind from the positive proposition that the net present value investment rule will lead to value creation.* —Michael Jensen (2009)

## 1. Introduction

In the modern era of fund-based asset management, most investment decisions are delegated to agents whose behavior and character are imperfectly observed and known. Trust is thus an essential feature of the principal–agent relationship in the investment industry and integrity is an important factor in delegated fund management. A variety of institutions have developed to mediate the trust relationship, including regulators, independent auditors, third-party due diligence firms, and informal word-of-mouth networks. Each time a manager "touches" one of these institutions, verifiable information is generated. The consistent or contradictory nature of this information has the potential to enhance or reduce the perceived trustworthiness of the manager.

The issue of trust is particularly important in the hedge fund industry. Prior to the Dodd-Frank Act of 2010, many U.S. domiciled hedge funds registered with the U.S. Securities and Exchange Commission (SEC) on a voluntary basis only. Information about funds is thus often limited to qualified investors who review the fund offering memoranda or the narrow, voluntarily provided information in public databases. Fund advisors have therefore historically relied on trusted referrals as a prime distribution channel. This reliance on referrals and typically limited transparency are potential reasons why the Madoff scheme lasted so long. Relatively few third-party entities had access to performance statistics and operational information. In an environment lacking multiple, comparable sources of information about an agent's credibility, trust is even more important, as are mechanisms to verify trustworthiness.

Brown et al. (2008b) examine the limited disclosure that most U.S.-based hedge funds were obliged to make due to the requirement to register as investment advisors for a brief period in 2006. The authors show that prior to this date, sophisticated investors already understood the substantive content of subsequently mandated disclosures. Furthermore, by examining the cross-sectional correlates of these disclosures, they derived an indirect measure of operational risk based solely on information contained in public access databases. Brown et al. (2009) validate this measure on an out-of-sample basis by showing that it predicts subsequent poor performance and fund failure.

However, this research does not describe how sophisticated individuals come to understand these operational risk issues prior to the 2006 public disclosure. Also, the Form ADV that each fund submitted to the SEC contained relatively little information. For this reason it is not clear whether this TASS-based measure of operational risk derived on the basis of correlation with Form ADV disclosure truly reflects inadequate or failed internal processes. Perhaps it represents a distinct but related phenomenon. In addition, the minimum asset requirement of $25 million to file Form ADV excluded many small, potentially problematic funds that, for example, may not have even been able to afford reputable auditors (Liang (2003)).

This paper uses detailed evidence on failed internal processes, people, and systems to derive a more direct measure of operational risk, consistent with the Basel definition of operational risk. According to the Basel Committee on Banking Supervision (BCBS), operational risk is defined as "the risk of direct or indirect loss resulting from inadequate or failed internal processes, people and systems or from external events" and is to be distinguished from systemic, strategic or reputational risk (BCBS (2001)).

In particular, we analyze a database of due diligence (DD) reports on hedge funds provided by a major DD firm. These DD firms specialize in gathering and verifying information potentially relevant to the assessment of hedge fund operational risk. This information is potentially valuable since, according to Capco (2003), operational risk is responsible for over half of reported hedge fund failures. While the academic literature has widely studied the roles of regulators, auditors, and informal reputation within financial markets, research on third-party investigation is comparatively recent. The novel feature of the DD reports for our purpose is that they document in detail inadequate or failed internal processes, factual misrepresentations, and inconsistencies in statements and materials provided by hedge fund managers. Thus, we are able to use these reports to derive a direct quantitative measure of operational risk.

We find that operational issues do indeed lead to direct and indirect losses, consistent with earlier studies. In addition, we are able to document which internal process failures contribute most to a relevant definition of operational risk. Finally, the general lack of operational transparency and the evidence of operational problems these reports reveal should itself be a source of concern to many investors. Based on the above, this paper considers four broad questions.

First, do hedge fund managers accurately represent material facts to their investors? We focus on statements made about past regulatory and legal problems, and upon verification problems relating to valuation and performance. The former is pertinent to the potential for future operational events, and the latter is important because it is relevant to the reliability of investor returns. We find that reporting issues are significantly associated with measures of operational risk. Second, we ask whether the DD process successfully identifies inadequate or failed internal processes. We find that failure to use a well-known accounting firm, reliance on internal pricing, and inadequate signature controls are associated with operational risk.

Third, we build a simple canonical correlation-based measure of operational risk. Unlike the indirect measure of operational risk used by Brown et al. (2008b), our new measure of operational risk is based on evidence of imperfect or failed internal processes taken directly from the DD reports themselves, including data on informational contradictions and variables related to honesty. We then validate this measure of operational risk by out-of-sample tests that show that exposure to this risk increases the likelihood of poor subsequent performance and fund death.

One important consideration is that we do not have DD reports for every hedge fund in the industry. Generally, investor interest will gravitate toward those funds with good performance, which is evident in our sample of DD reports. Our measure of operational risk addresses this issue by constructing the canonical correlates of operational risk using a multivariate extension of Heckman's (1979) procedure, which is described in Appendix B, to obtain a consistent estimator of the covariance matrix of the variables of interest that is not conditional on the way in which the sample was selected. By doing so, we not only address the selection bias issue in this operational risk context, but also provide a pathway for future researchers to utilize the canonical correlation procedure in settings with selection bias.

Finally, we find evidence that exposure to operational risk does not appear to be a factor influencing investor decisions. A flow–performance analysis indicates that investors chase past performance regardless of operational risk exposure. These results confirm findings of Brown et al. (2008b) that are based on an analysis of Form ADV filings required of U.S. domiciled funds in 2006.

Using a slightly smaller subset of the data we employ in this study, Cassar and Gerakos (2010a) document correlation between hedge fund internal controls and manager fees, arguing that the extent of operational risk controls is endogenous. Cassar and Gerakos (2010b) find that, while pricing controls impact return smoothing, the major driver of return smoothness is asset liquidity. Besides focusing on the topic of manager trust and operational risk's impact on performance and flows, rather than the determinants of fund controls, this paper also controls for which funds are selected for DD reports, an issue not addressed in Cassar and Gerakos (2010a, 2010b). We find evidence of significant selection bias and show how to address this issue in constructing measures of operational risk from the sample.

The remainder of the paper is organized as follows. Section 2 describes the data. Section 3 presents our results on operational risk analysis, manager integrity, fund performance, and flow–performance relation. We develop a univariate measure of operational risk that we validate on an out-of-sample basis by examining its relation to subsequent survival, performance, and future cash flows into the fund. Finally, Section 4 concludes the paper.

## 2. DD sample information

### *2.1 Data*

Our sample consists of 444 DD reports compiled by a third-party hedge fund DD service provider, HedgeFundDueDiligence.com. These funds are managed by 403 distinct advisors over the period 2003–2008. The DD report information is gathered by the company through several channels: the offering document and marketing materials provided by the manager, on-site interviews with the manager, and forms filled out by the manager. These data are augmented by verifying operational controls, assets under management and fund performance with the administrator. Finally, HedgeFundDueDiligence.com attempts to verify the authenticity of the audit with the auditor and perform a background check on the management company and its key staff.

A typical DD report costs $12,5000 and spans between 100 and 200 pages, with both quantitative and qualitative sections prepared for the clients. Typical clients of DD companies are mainly funds of hedge funds, but also include investment banks, family offices, and other institutions. These clients are usually considering an investment in the hedge fund and wish to gather additional information. Conventional databases such as TASS and CISDM provide fund-level information such as strategy, performance, assets, fees, and leverage, but they do not document the investment and operational process in any specific detail.

In contrast, DD reports reveal how portfolio values are determined, where the day-to-day accounting is done, how the DD firm verifies the accuracy of the data provided, and how the governance and control processes are conducted. As a result, the DD reports provide a natural platform for us to study operational risk. Both Capco (2003) and Brown et al. (2009) note operational risk is a major factor in hedge fund failures, even more so than financial risk. By hand-collecting data from the DD reports, we create

45 variables for our analysis, although not all data are available for all funds. For example, as noted by Aragon, Liang, and Park (2009), most onshore funds are organized as partnerships, which do not have boards of directors. Appendix A reports the data definitions for these variables.

We supplement the information collected by the DD company with data from a combined TASS/CISDM dataset. These two datasets are matched via names and other characteristics. If a fund exists in both CISDM and TASS, we default to the characteristic and return data provided in TASS. As of March 2009, TASS has a total of 12,656 funds and CISDM has 13,171 funds, both live and defunct. We are able to match 5,879 TASS funds and CISDM funds, which leaves us a combined hedge fund database of 19,948 unique funds. Our analyses focus on fields that overlap between both datasets. We use the style definitions utilized by Agarwal et al. (2008) for our combined dataset. Using this matched dataset, we then match the DD funds via fund names. If we are able to match a DD fund to our TASS/CISDM merged dataset, we rely on the performance information in the TASS/CISDM database for our performance and flow analyses.

In addition to specific funds investigated by the DD company, some advisors also manage other hedge funds besides those in the DD dataset. These funds are listed in the same DD report, along with information indicating if they are offshore, onshore equivalents, or part of the master-feeder structure of the fund being investigated. In the cases where the “other” funds listed on the DD report are distinct, we also add these funds to our sample when investigating performance and fund death. Since these funds are being operated by the same managers, they are arguably exposed to the same operational risks.[1]

*2.2 DD summary information*

One of the novel features of the DD data is that it allows for documentation of how back-office hedge fund processes are performed as well as summary information on the number of problems and measurement of trust between hedge fund managers and their investors. Of particular interest are variables related to operational issues that were previously unavailable in standard hedge fund databases. Using the DD sample, we present summary statistics on these new measures for the DD funds in Table 1.

<Insert Table 1 about here>

The first set of variables of interest is the fund's method of pricing securities. Hedge funds that invest in infrequently traded securities cannot rely solely on observed market prices and may supply their own estimates of these securities' prices. This method has obvious potential for operational risk or downright fraud if employed by an untrustworthy manager. If securities in the fund are priced either entirely or partially by the manager, we set *Pricing* equal to zero; if securities are priced completely externally, the variable is equal to one. Related to pricing is *NavRestate,* which indicates if the fund's net asset value has been previously restated and is a related indicator of the reliability of the pricing mechanism.

[1] These other funds may have some operational qualities that do not match the DD fund. We ran all performance and flow analyses on the DD funds only and reached conclusions similar to those presented in the text.

Another group of four variables evaluates fund signature controls. Two variables indicate the number of signatures required to move money from a bank or the prime broker. Generally, the more signatures required to move money, the lower the operational risk. However, the requirement of multiple signatures may be of little value if signatures are non-independent. To supplement these signature measures, the DD company also indicates whether money movements are restricted to certain locations. For example, money movements from the prime broker may be limited to only the fund's bank account. The DD company also indicates if the signature controls are "institutional quality," which the company defines as all money movements requiring an internal and independent third-party signature. The DD company uses this standard to compare the fund's signature controls against a predefined standard rather than to render an opinion.

Two of the DD variables address personnel and governance. The number of staff departures relates to the risk involved when know-how is lost or continuity in oversight is compromised. Higher personnel turnover taxes other staff's attention and is a common red flag for operational risk. The percent of independent board members is a standard governance measure that equates independence with disincentive for fraud and lack of conflicts of interest. It has been shown to be a useful variable in studies of the mutual fund industry (see Cremers and Nair, 2005). Additionally, the possible unwillingness of an independent director to serve on a board is an indication of potential problems.

The DD firm also reports whether the fund is audited by a Big 4 accounting firm. Importantly, the fund "inherits" the positive reputation of the firm to the extent that the auditor issues an unqualified opinion with respect to audited assets and valuation procedures. In the aftermath of the Enron case, which brought down a major accounting firm, the risks to the auditor of taking on an untrustworthy client are clearly evident. Thus, this simple variable is expected to carry considerable weight in separating funds with and without significant risk of fraud.[2] Because of this liability, the auditing firm typically pre-screens managers for the potential risk they pose the firm before taking them as a client. In fact, one of the DD report states, "*OneBig4Auditor* performs extensive due diligence prior to accepting a new client." Because of client confidentiality issues, audit firms are not a public source of information about manager operational risk.[3]

One key operational risk variable is whether or not the fund has had a previous regulatory issue or lawsuit ("problem"). Brown et al. (2008b) find problem funds have significantly more conflicts of interest compared to non-problem funds. This suggests that the potential for exploiting customers is associated with past adverse events. The DD company also asks managers to disclose any past legal and regulatory problems. Rather than use open-ended questions that may be misinterpreted, the DD company uses a hard copy form consisting of several yes/no questions, which is also signed by the manager. Forty-one percent of the DD funds have had a problem, more than twice the frequency of problems reported in the 2006 Form ADV filings (Brown et al., 2008b). Specifically, 32% have been involved in legal disputes as defendants and 15% have had past regulatory problems. Firms with problems of this nature would be less inclined to reveal

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[2] Liang (2003) indicates that hedge funds that employ Big 4 auditors tend to be large funds and have fewer reporting discrepancies. Later work—not reported here—expands the definition of what constitutes a major accounting firm to include any firm retained by five or more hedge funds. All results are of similar statistical significance, but slightly smaller in economic magnitude. This supports this reputational hypothesis.

[3] Auditors were unresponsive to all DD company questions except for the most basic requests for information. Major auditors, including the Big 4 and other specialized auditors for hedge funds, would not discuss any aspect of their audits with the DD company, even going as far in some cases as to refuse to confirm the fund was a client of the company. This was regardless of whether or not the fund gave the auditor permission. In some circumstances, the DD company was able to obtain audits from either the administrator or the fund itself to help verify performance and asset information. However, without auditor verification, the DD company would be unable to verify the authenticity of the audit.

them publicly through registration. Unscrupulous managers might even misrepresent the extent of past problems to customers.

Fee-based DD service providers seek to capture this kind of misrepresentation by comparing a manager's statement about past legal and regulatory events to third-party records and note whether the manager's account squared with the independent evidence. These third-party records can come from auditors, administrators, custodian, or prime brokers. Misrepresentation of a manager's background also falls into this category. In this sample, 21% of funds had a misrepresentation. The DD company also indicates if it could not verify other information provided by the manager, which includes discrepancies relating to operational issues such as the signatures required for fund transfer. The manager may report that the fund uses one procedure and the bank or broker may report that the fund uses another. The category *Noted Verification Problem* indicates that 42% of the funds in our sample had either a misrepresentation or an inconsistency problem.

*2.3 Summary statistics of DD problems*

The results in the prior section document many DD funds have experienced past problems as well as significant issues verifying information provided by hedge funds. To further investigate these infractions, we report results in Table 2 for subcategories of problems and misrepresentations. *Signature Disagreement* indicates that in 16% of the cases, the fund's and administrator's versions of the signature process did not match, while *Pricing Disagreement* indicates that 3.6% of the funds disagreed with the administrator on portfolio pricing process. Also, 11.5% of the funds switched a major service vendor in the last three years (*Switched Vendor*), while 14% of the funds or their administrators refused to answer DD company questions (*Refused DD Question*).

<Insert Table 2 about here>

In the wake of the Madoff scandal, verifying the performance and existence of assets has taken on greater importance.[4] Surprisingly, about 18% of funds' asset information either could not be verified independently (*Can't Verify Assets*) or disagreed with evidence from an alternative source (*Assets Disagree*). Similar performance related discrepancies (*Performance Disagree*) or verification problems (*Can't Verify Performance*) were noted for 14% of DD investigations. The DD firm also found that 21% of managers (*Bad Recall*) interviewed verbally stated incorrect information to the DD company when checked against written documentation, including poor recollection about basic levels of assets and performance. For example, one manager's verbal assets under management figure was over $300 million higher than the actual number.

We found it useful to rank how forthcoming managers were concerning their past problems, and consider three cases. In the first case, managers voluntarily disclosed a past problem; however, after further investigation, the DD company found additional undisclosed past problems. This occurred in six percent of the cases, and we label these as strategic misstatements in Table 2. In the second case, managers disclosed no past problems, but the DD company found they had past problems. This occurred nine percent of the time, and we simply label these as misstatements. Finally, if a fund disclosed past problems and the DD company found these were all of the past problems, with no additional misrepresentations concerning their backgrounds, we labeled these managers

[4] "It's very easy if you want. You must do a third-party check. It's an absolute must," Mr. Madoff said of how one investigates a Ponzi scheme. "It's Accounting 101." *Wall Street Journal*, October 31, 2009.

as truth tellers (23%). It is remarkable that about 16% of funds in the sample intentionally or unintentionally misstated material facts to the DD company, even when they knew that the company was hired to verify this information.

To investigate the relation between funds' operational properties and past problems, we separate out problem funds from non-problem funds and report mean fund characteristics and differences in means in Table 3.

<Insert Table 3 about here>

We find little difference in the performance of the two groups. Problem funds tend to be larger than non-problem funds, which may be a function of larger funds having more opportunities for lawsuits. These findings are consistent with Brown et al. (2008b). We do find non-problem funds have some better operating controls. Non-problem funds use independent pricing procedures more frequently than problem funds, although the latter are also more illiquid (measured by longer lockup and redemption periods) and therefore may have to rely more on internal pricing. Also, non-problem funds are more likely to have a Big 4 auditor, which is particularly interesting in light of the practice of auditors pre-screening clients through their own DD process. Finally, problem funds are more likely to have switched data vendors, perhaps because irregularities may have been discovered by the previous vendor.

## 3. Measuring operational risk

### *3.1 Relationship between fund problems and operational characteristics*

Potential hedge fund investors must decide whether to trust managers with their money. An important question for investors is whether a fund's operational controls compensate for any potential historical breaches of trust. For example, if managers have past problems, then strong operational controls may alleviant investors' concerns. In addition, if a relation between problems and operational controls exists, then simply having information about the background history of the managers may provide investors with some comfort regarding a fund's operational controls.

To test these propositions, we examine the relation between past problems and operational controls using a logistic model. However, one confounding aspect in any empirical analysis is the potential for selection bias. Unlike the TASS/CISDM database, which comprises thousands of hedge funds, we only have the results for the 444 funds the DD company examined at the specific request of a potential or current fund investor. Previous research, such as Getmansky, Liang, Schwarz, and Wermers (2010), finds investors are more likely to invest in hedge funds that have certain characteristics, such as higher historical performance. Investors may also be more likely to request a DD report when they do not trust self-reported historical performance. For these reasons, our DD sample may not represent a random sample of funds from the entire hedge fund universe. We control for selection bias by performing the analysis using a two-stage Heckman (1979) model. The *lambda* term represents the inverse Mills ratio obtained from the first-stage regression.[5] The second-stage logistic model utilizes advisor information to cluster

[5] In unreported results, we run a selection model to determine if the observable information before a DD report, i.e. the characteristic and performance data available in TASS and CISDM, is able to explain the investor selection process. Indeed, we find that DD selection is significantly related to several fund characteristics, most importantly high performance and size prior to the DD report. These results are consistent with the previously found performance chasing behavior of hedge fund investors. Also, abnormally high returns that may encourage investor interest and lead to the commissioning of a DD report

standard errors and also includes style dummies. In this model, positive coefficients indicate a higher likelihood of problems. The results are reported in Table 4.

<Insert Table 4 about here>

We find that funds with past problems have poorer operational controls. Problem funds are less likely to have independent pricing. Problem funds are also more likely to have switched vendors in the last three years. While changing vendors to upgrade service quality is positive for investors, changing vendors may also be a red flag, since the fund may have been dropped by the previous vendor due to data inconsistency. Finally, problem funds are less likely to have a major auditor. Reputational concerns may lead major auditors to be reluctant to accept funds with legal or regulatory issues as clients. This evidence is consistent with Brown et al. (2008b), who find that operational risk (measured by the probability of having problems) is positively associated with conflict of interest and concentrated ownership. We would expect that having a major auditor and independent pricing would be negatively associated with conflicts of interest.

One potential drawback of using background information on managers is the reliability of this information, especially if it is self-reported. Indeed, approximately 20% of funds' managers misrepresented past problems or their background information. A total of nine percent of funds would have been classified as non-problem funds based on the information disclosed voluntarily to the DD company, but were found to be problem funds after background checks by the DD company.[6]

may also be evidence of operational risk due to fraud. (We thank Paul Woolley for this observation.) We use this model as the first stage of the Heckman (1979) procedure.

[6] In results not reported here but they are available upon request, we find that not having a major auditor is strongly correlated with the probability that the fund misrepresents material facts to the DD company. This relation may again be due to the fact that major auditors would most likely perform a standard DD before accepting such funds as clients.

*3.2 Canonical correlation analysis*

The incidence of past problems is only one aspect of operational risk. The DD forms contain many variables described over hundreds of pages. The Basel definition assumes that it is possible to reduce the dimensionality of this problem to a single quantity referred to as operational risk. For default risk, Altman (1968) reduces its multiple dimensions using a discriminant analysis to derive the univariate Altman *Z*-score, which has proved useful in predicting corporate financial distress. Similarly, as noted previously, Brown et al. (2008b) propose a univariate measure of operational risk based on indirect but observable variables. Since we have a far more extensive database of operational problems that are distributed through time for each fund, we are able to extend and refine this analysis by constructing a measure of operational risk from direct evidence of failed processes, people, and systems. This measure is computed as the linear combination of operational characteristics that maximally correlate with factors shown to contribute to fund failure.[7]

To apply this method to the DD database, we first identify a set of TASS variables related to fund death noted in previous literature (Liang, 2000; Brown et al., 2001): average monthly returns from the previous year, the monthly standard deviation and first-order autocorrelation from the previous year, the size at the beginning of the period, fund age, fees, leverage, lockup provision, and the advance notice period. Next, we form a linear combination of these TASS variables that maximally correlate to the set of the DD

[7] Brown et al. (2008) construct their operational risk measure from TASS data instead of the ADV information, since hedge funds were only obliged to register as investment advisors and file the required Form ADV for a brief interval in 2006. However, as the authors argue, informed investors already knew the substantive content of the Form ADV disclosures before they became public because they had access to more extensive private information sources. This study constructs a measure of operational risk directly from these private information sources.

variables we have considered.[8] The maximum correlation between the two linear combinations is 0.47. Finally, the resultant linear combination of the DD variables provides the desired single operational risk measure, which we refer to as an $\omega$-score.

<Insert Table 5 about here>

Table 5 indicates that funds with better past performance have lower operational risk; funds with smoothed returns (lower standard deviation) display higher operational risk; younger and smaller funds suffer from higher operational risk; and high-quality managers (signaled by higher management and incentive fees, as well as the use of leverage) are associated with lower operational risk. Finally, funds with longer lockup and advance notice periods generally invest in illiquid assets, so the managers have more discretion in smoothing returns or pricing portfolios, and hence higher operational risk. Cassar and Gerakos (2010b) find funds using fewer independent pricing sources and with greater managerial discretion in pricing portfolios are more likely to smooth returns, which supports these findings.

In terms of the DD variables, the variables relating to misstatements and internal accounting are all positively related to operational risk. In contrast, the use of a major auditor and external pricing significantly reduce operational risk.[9] Large and well-

[8] To address sample selection concerns, the canonical analysis is based on a consistent estimator of the unconditional covariance matrix of the variables using a multivariate extension of the procedure described in Heckman (1976). Following the same argument that Heckman makes, the covariance matrix estimated in this procedure is a consistent estimator of the true unconditional covariance matrix and by extension, the canonical correlates are also consistent on which the statistical significance is determined. We have not examined the finite sample properties of this estimator and, thus, one must be careful interpreting the measures of statistical significance reported in Table 5.

[9] Big 4 status does not indicate that other accounting firms are incapable of performing a satisfactory audit. Indeed, many hedge funds prefer to use specialist accounting firms for this purpose. We repeat the analysis using a measure of whether the accounting firm is used by at least five other hedge funds. The results are almost identical, although slightly weaker, pointing to the certification role Big 4 auditors may provide

established firms may take on a certain reputational risk by accepting funds with poor operational controls as clients. In addition, such funds may be less willing or able to retain a major auditing firm.

### *3.3 Operational risk and subsequent fund performance*

The results in the previous section show a relation between operational risk and problems, similar to that in Brown et al. (2008b, 2009) on hedge fund operational risk. A key difference is that we are able to construct an operational risk $\omega$-score based directly on the extensive data contained in the DD report itself. In addition, while those studies examine the relation between operational risk and potential conflicts of interest, the collected DD data provides the opportunity to examine other potential operational risks for investors. In light of the recent Ponzi-scheme scandals in the hedge fund area, one issue of great interest is whether reported returns fairly represent investor performance. Prior research on hedge fund performance identifies evidence consistent with the view that some hedge fund managers game their performance (see, e.g., Bollen and Pool (2009); Getmansky et al. (2004); Agarwal et al. (2011)).

We validate the $\omega$-score as a measure of Basel-defined operational risk by an out-of-sample test that shows that exposure to this measure of risk leads to an increased likelihood of subsequent poor performance which cannot be otherwise explained by market risk exposure. For each fund in our sample, we compute the post-DD report appraisal ratio, which is alpha measured in units of the standard deviation of excess returns, using the seven-factor model of Fung and Hsieh (2004).[10] The seven-factor

[10] We thank David Hsieh for making this data available at his website, http://faculty.fuqua.duke.edu/~dah7/HFData.htm. The use of the appraisal ratio has become standard in the

model includes two equity factors, two bond-oriented factors, and three trend-following risk factors developed based on Fung and Hsieh (2001). In Table 6 we regress this performance measure on operational risk and other fund characteristics, controlling for selection using the two-step Heckman (1979) procedure.[11]

<Insert Table 6 about here>

As Brown et al. (2008b) find, operational risk leads to low subsequent performance. All else equal, a one-unit increase in the omega score of a fund is associated with approximately a 0.26 decline in the fund's appraisal ratio after the DD report. Given the average appraisal ratio in the post-DD period is 0.21, this is an economically significant impact. Similarly, a one unit increase in the omega score of a fund is associated with a significant 0.08% to 0.11% decline in monthly alpha as reported in Appendix C. In other words, by using the information provided in the DD report, investors could forecast subsequent risk-adjusted performance. These findings are robust to the inclusion of style dummies as well as the inclusion of fund size and age.

We interpret the negative sign on the standard deviation and its interaction with operational risk to indicate that funds with abnormally low reported standard deviations may have smoothed prior returns. The significance of the inverse Mills ratio tells us that

empirical hedge fund literature. Much of the cross sectional dispersion in alpha is explained by significant differences in the use of leverage within the hedge fund universe. The appraisal ratio on the other hand is invariant to leverage (Agarwal and Naik (2000). We also considered the Hsieh–Fung alpha computed using these benchmarks as a measure of performance, with very similar results reported in Appendix C.

[11] The residuals in the second step of the Heckman procedure are heteroskedastic and we must also account for the fact that the inverse Mills ratio (lambda) is measured with error. This issue is discussed in Greene (2003) pp. 784-785. To account for this we use the clustered standard error procedure (Liang and Zeger 1986). which is heteroskedasticity-consistent. We also considered an extension of the standard Greene asymptotic covariance matrix (Greene 2003 p.285) adapted to this cluster correlated application with very similar results.

we might question the high returns and low volatility of returns that led to the DD report being commissioned in the first place.

### *3.4 Relation between operational risk and fund death*

Consistent with the Basel definition, operational risk as we define it leads to direct and indirect losses that can be measured in terms of diminished performance. In extreme circumstances operational failures can lead to fund failure. There can of course be many reasons why a fund might disappear. Particularly during the recent financial crisis, many funds closed due to a sharp decline in assets under management as a result of both poor performance and large investor withdrawals. At the same time, the financial crisis revealed operational deficiencies at many funds, an example being the funds of funds associated with Madoff. On the basis of data prior to the crisis, Brown et al. (2009) argue that excess financial risk may in fact be evidence of poor operational controls, and that operational risk provides a better explanation of fund death than does financial risk, although the two are obviously related.

Our data prevent us from addressing this issue directly. While we have more complete data on operational characteristics, we have no information on many DD funds' subsequent history. Even for funds matched to TASS or CISDM, as Getmansky, Lo and Mei (2004) note, failure to continue reporting does not necessarily indicate fund death. Perhaps the fund stopped reporting because they closed to new investment or merged with another fund. TASS indicates why funds stop reporting and we can therefore properly identify dead funds if they report to TASS. We define dead funds as those with defunct codes in the most recent version of TASS of liquidated, dormant, where the fund is closed down or where TASS is unable to determine the reason for the failure to report data. We otherwise consider the fund alive. Using this definition of fund death, we are able to show that operational risk increases the probability of fund failure among this subset of DD funds. However, given the small sample of funds for which we have reliable data, we cannot determine the magnitude of this probability with statistical precision.

One approach to increase the available sample size is to exploit the duality of the canonical correlation analysis to calculate a measure of operational risk based on observed TASS variates that correlate to the operational characteristics of the funds in our sample.[12] In this way, using the TASS database of January 2003, we can construct a measure of operational risk for every U.S. Dollar dominated fund alive as of that date with sufficient data, and ask the question whether high operational risk as of that date predicts fund failure over the period of our sample. Since this measure of operational risk is not directly based on fund characteristics but rather on the observed TASS correlates it may not be very precise. We therefore define high operational risk as an implied ω-score greater than the median value of that quantity across all funds in the sample. The results reported in Table 7 show that operational risk derived originally from the DD data and mapped into the TASS variable space indeed substantially increases the likelihood of fund death and that, as expected, there is a significant interaction between operational risk and financial risk.

<Insert Table 7 about here>

*3.5 Relation between operational risk and future flows*

[12] We thank an anonymous referee for this suggestion.

We find that operational risk characteristics that are revealed in the DD report indicate lower than expected future returns and are a leading indicator of fund failure. Is operational risk a factor investors consider when allocating assets among hedge funds? Some individuals invested with Madoff even when they understood his operational deficiencies, including using an unknown accountant to audit what was a $17 billion fund according to his Form ADV filing. Brown et al. (2008) find no relation between investor flows and operational risk disclosed by hedge funds during the brief period of mandatory disclosure by the SEC. However, ambiguity exists as to whether investors ignored operational risk concerns or simply did not know them. While the DD reports are specifically prepared for one investor, clients and data subscribers are allowed to view other reports for a fee. This information will likely be known to other clients and third parties either interested in investing or already invested in the fund, and can potentially filter through third-party channels and become "public" information in the investment community. In cases for which the information goes no further than the original client, we might still expect to observe significant investor response since the largest DD fund investor represents 21% of assets on average.

To examine investor behavior, we focus on the extent to which the measure of operational risk mediates the flow–performance relation that has been documented for mutual funds and hedge funds. We follow the procedure of Sirri and Tufano (1998), except we define prior return ranking and subsequent annual flows relative to the date of the DD report. In other words, for each DD fund, we track back a minimum of nine months and a maximum of 12 months of complete return data. We then select every fund in the TASS/CISDM universe that has returns during the same time period. We define the ranking of this DD fund among all other funds available in the same time period. Table 8 shows that, while flows are strongly and positively related to high past performance, the measure of operational risk based on DD fund characteristics does not influence these flows in any way no matter whether we look at the operational risk term or the interaction terms with performance ranks. Our results here reinforce the finding by Brown et al. (2008b) that operational risk does not mediate the tendency of naïve investors to chase past performance. In addition, the lambda variable is significant, indicating that DD funds are selected based on large amounts of investor flows.

<Insert Table 8 about here>

As a final examination of investor reaction to the DD reports, in Table 9, we compare the levels of money flows directed toward the DD funds after the DD reports with those of funds of similar size, age, and performance in the same style prior to the DD report date. On the one hand, we know investors are interested in these funds; thus the DD funds should have higher levels of flows. However, all DD reports find some level of red flags, which may deter investment.

<Insert Table 9 about here>

On average, DD funds do have higher investor flows after the DD reports. Thus, most investors must still feel comfortable enough to invest in these funds. Investors may use the DD report as one of the screening criteria, together with their own information and connections. Interestingly, the mean flow received by problem funds is higher than that received by non-problem funds, although the difference between the two groups is not significant. These findings, which are similar to the results reported previously using the $\omega$-score, emphasize that even problems themselves do not slow investor flows.

## 4. Conclusion

Using hand-collected and proprietary data of 444 hedge fund DD reports from a major due diligence company, we study operational risk, manager integrity, and the relation between hedge fund performance and investor flows. Despite the fundamental importance of integrity in the delegated asset management business, we find that incomplete and inaccurate disclosure of important information is not uncommon among a sample of funds selected for scrutiny by clients of a major DD firm.

In this context, we derive a simple univariate measure of operational risk that is consistent with the Basel definition of this term and based on direct evidence of failures of processes, people, and systems made evident in the DD reports. This measure is based on the extent to which these failures correlate with factors that have been shown to relate to fund failure. The ability to derive a simple univariate measure has important implications for corporate, accounting, and regulatory applications, where simple operational risk measures are currently lacking. It is important to control for the non-random selection of hedge fund for DD scrutiny, and our measure of operational risk is based on a new canonical correlation-based procedure that corrects for this selection bias through extending Heckman's (1979) procedure as are our other empirical results. This is useful for future studies in relating to the selection bias issue.

After controlling for the selection bias, we find that unwillingness to be forthcoming about past legal or regulatory problems and the failure to use a well-known auditing firm are leading indicators of operational problems. These findings strongly suggest that information verification is an important offering in the market for investment services, especially for hedge funds and other lightly regulated service providers. Despite its potential usefulness, we do not find any evidence that exposure to the operational risk metric mediates investors' return chasing behavior. In other words, operational risk does not appear to be a material concern to investors even though high operational risk can potentially destroy investor value. This further validates the important need for educating investors through establishing some quantitative risk models such the $\omega$-score.

In prior work, Brown et al. (2008a) hypothesize an important role for private sector information providers in the hedge fund industry. The current study allows for an in-depth examination of this private sector mechanism using a key subsample for which information gathering was costly and evidently of some value to the investor. Given that misrepresentation of material facts is found to be a leading indicator of poor future returns, these results emphasize the importance of operational DD in diversified hedge fund strategies adopted by institutional investors and high net worth individuals. Our results have important implications for areas beyond the hedge fund industry where delegation and trust are necessary.

## Appendix A. Data definitions

Data are from a DD company. There are 444 funds. All data were hand-collected.

| | |
|---|---|
| **Performance** | |
| Avg. returns | Average monthly return prior to the DD report in percent |
| Return std. dev. | Average return standard deviation prior to the DD report |
| Autocorrelation | Average return autocorrelation prior to the DD report |
| **Fund Properties** | |
| Management fee (%) | Fund's management fee in percent |
| Incentive fee (%) | Fund's incentive fee in percent |
| High water mark | 1 if the fund has a high water mark, and 0 otherwise |
| Redemption period | Number of days between redemption opportunities |
| Lockup period | Number of days new money is locked into fund |
| Notice period | Number of days request for a redemption notice |
| AUM ($ millions) | Assets under management at DD report time |
| Log(assets) | Log of assets in US dollars |
| Fund age | Age of fund in years |
| **Operations** | |
| Pricing | 1 if priced completely externally, 0 if mixed or internal |
| Signature: IQ | 1 if signature controls are institutional quality, 0 otherwise |
| Big4Auditor | 1 if fund's auditor is a Big 4 auditor, 0 otherwise |
| Money Restrictions | 1 if restrictions on where money can be sent from bank/PB |
| NAV restate | 1 if fund has restated NAV in the past |
| Staff departure | Number of persons that have departed the fund |
| % of board Ind. | Percentage of board members who are independent |
| Internal Accounting | 1 if fund uses day-to-day internal accounting |
| **Background Issues** | |
| Problem | 1 if fund has a lawsuit or regulatory problem, 0 otherwise |
| Lawsuit | 1 if fund has a lawsuit, 0 otherwise |
| Regulatory | 1 if fund has a regulatory issue, 0 otherwise |
| Misrepresentation | 1 if managers failed to disclose past regulatory or legal issue |
| Noted Ver Problem | 1 if DD company had a problem verifying information, including significant differences between performance/assets and operational rules and failing to disclose prior problems |

| Misstatement Information | |
|---|---|
| Strategic Misstatement | Fund voluntarily discloses a problem but does not disclose all problems |
| Misstatement | Fund discloses no problems, but has problems |
| Truth Teller | Fund discloses all problems |
| Regulatory Misstatement | Did not disclose all regulatory infractions |
| Lawsuit Misstatement | Did not disclose all lawsuits |
| Legal Misstatement | Did not disclose all legal problems |
| Background Misstatement | Misrepresented personal background information |
| | |
| Background Issues | |
| Signature Disagreement | Disagreement between fund and administrator on signature process to move money |
| Pricing Disagreement | Disagreement between fund, administrator, and/or auditor on process to price the portfolio |
| Bad Recall | Fund verbally said something incorrect during DD visit |
| Assets Disagree | Disagreement between fund, administrator, and/or auditor on asset information |
| Performance Disagree | Disagreement between fund, administrator, and/or auditor on performance information |
| Switched Vendor | Fund switched the vendor of a major process in the last three years. |
| Refused DD Question | Fund and/or administrator refused to answer a DD question |
| Can’t Verify Assets | DD company cannot independently verify asset information |
| Can’t Verify Performance | DD company cannot independently verify performance information |
| Perf Ver Problem | 1 if assets disagree, performance disagree, can’t verify assets, or can’t verify performance, and 0 otherwise |
| Oper Ver Issue | 1 if signature disagreement or pricing disagreement, and 0 otherwise |

## Appendix B. Multivariate extension of Heckman's (1979) procedure to address selection bias in the canonical correlation estimator

Heckman (1979) addresses the problem of drawing inferences from statistical models where the data are drawn subject to a particular sample selection rule. His results apply to the simple bivariate case, but it is a straightforward matter to extend his results to the multivariate case which applies in the case of a canonical correlation estimator.

Standard results from Kotz, Balakrishnan, and Johnson (2000) establish that if $X_i = \mu_i + \sigma_i Z_i,\ i = 1..K$, where $Z_i$ are standard normal variates with covariance $Cov\,[Z_i, Z_j] = \rho_{ij},\ i,j = 1..K$, and $Z_1$ enters into the sample selection rule, $X_i, X_j | Sample\ Selection\ Rule,\ i,j = 2..K$, are multivariate normal with means $E[X_i|Sample\ Selection\ Rule] = \mu_i + \sigma_i \rho_{1i} E[Z_1|Sample\ Selection\ Rule]$, variances $Var\,[X_i|Sample\ Selection\ Rule] = \sigma_i^2(\rho_{1i}^2 E[Z_1^2|Sample\ Selection\ Rule] + 1 - \rho_{1i}^2)$, and covariances $Cov\,[X_i, X_j|Sample\ Selection\ Rule] = \sigma_i \sigma_j \big(\rho_{1i}\rho_{1j} E[Z_1^2|Sample\ Selection\ Rule] + \rho_{ij} - \rho_{1i}\rho_{1j}\big)$.

If the sample selection rule implies that we only observe $X_i, i = 2..K$, for $Z_1 > \theta_t = -w'_t\gamma$, then, following Heckman (1979), we have $E[Z_{1t}|Sample\ Selection\ Rule] = \lambda_t = \phi(\theta_t)/\Phi(-\theta_t)$ and $E\,[Z_{1t}^2|Sample\ Selection\ Rule] = 1 - \delta_t$, where $\delta_t = \lambda_t(\lambda_t - \theta_t)$. Under these conditions, $E[X_{it}] = \mu_i + \sigma_i\rho_{1i}\lambda_{1t}$, $Var\,[X_{it}] = \sigma_i(1 - \delta_t\rho_{1i}^2)$, and $Cov\,[X_{it}, X_{jt}] = \sigma_i\sigma_j\big(\rho_{ij} - \delta_t\rho_{1i}\rho_{1j}\big)$.

Following Heckman, we can then obtain a consistent estimator of the unconditional covariance matrix of the observations defined by $\sigma_i, \sigma_j, \rho_{ij}$ by first estimating the probit equation to obtain maximum likelihood estimates of $\gamma$ and computing $\hat{\lambda}_t = \phi(w'_t\hat{\gamma})/\Phi(w'_t\hat{\gamma})$ and $\hat{\delta}_t = \hat{\lambda}_t(\hat{\lambda}_t - w'_t\hat{\gamma})$. Then by regressing each $X_{it}$ on a constant and $\hat{\lambda}_t$, we can obtain estimates of each $\sigma_i\rho_{1i}$, and, using the result that $plim\ \frac{1}{T}\sum_{t=1}^{T}\hat{\delta}_t = \bar{\delta}$, we can obtain consistent estimators of $\sigma_i, \rho_{1i}, \rho_{ij},\ i,j = 2..K$, using $\hat{\sigma}_i = \sqrt{\widehat{Var}X_i + \bar{\hat{\delta}}\,\widehat{\sigma_i\rho_{1i}}^2}$, $\hat{\rho}_{1i} = \frac{\widehat{\sigma_i\rho_{1i}}}{\hat{\sigma}_i}$, and $\hat{\rho}_{ij} = \frac{\widehat{Cov}\,X_iX_j}{\hat{\sigma}_i\hat{\sigma}_j} + \bar{\hat{\delta}}\,\hat{\rho}_{1i}\hat{\rho}_{1j}$. We can then compute consistent estimators of the unconditional canonical correlation coefficients using the appropriately partitioned estimator of the unconditional covariance matrix computed in this manner (see, e.g., Press, 1972).

### Appendix C. Relation between the post-DD alpha and operational risk measure $\omega$-Score

Investigating the relation between the alpha measured after the DD report and risk measures computed as of the date of the DD report, this table reports *t*-values computed on clustered (on style of management) standard errors. The standard deviation is the natural logarithm of the monthly return standard deviation up to but not including the report dates. Both DD funds and their related funds are included in the analysis. In Panel A, the fund alpha, computed using the Fung–Hsieh (2004) seven-factor model using returns after the DD report, is the dependent variable. In Panel B, the difference between the fund's alpha and a matched fund's alpha after DD report period for the DD funds is the dependent variable. Matched funds are selected based on age, size and performance in the period prior to the DD report. Models are run in connection with a two-stage Heckman (1979) model, where *Lambda* is the inverse Mills ratio. Here ** and * indicate significance at the 1% and 5% levels, respectively.

**Panel A: Post-DD Report Alpha**

| | Model 1 | | Model 2 | | Model 3 | |
|---|---|---|---|---|---|---|
| | Coeff. | *t*-value | Coeff. | *t*-value | Coeff. | *t*-value |
| Intercept | 0.065 | 0.12 | -0.045 | -0.12 | 1.813 | 1.77 |
| Omega | -0.078 | -4.17** | -0.081 | -3.05** | -0.105 | -2.96** |
| Prior Std. Dev. | -0.018 | -0.17 | 0.003 | 0.03 | 0.008 | 0.07 |
| Omega* Std. Dev. | -0.019 | -4.48** | -0.021 | -3.70** | -0.025 | -3.60** |
| Directional Traders | | | 0.249 | 11.85** | 0.299 | 5.54** |
| FOF | | | 0.041 | 0.59 | 0.076 | 0.79 |
| Managed Futures | | | 0.726 | 11.97** | 0.637 | 13.62** |
| Multi-Process | | | 0.362 | 8.23** | 0.438 | 5.76** |
| Relative Value | | | 0.248 | 3.72** | 0.344 | 3.15** |
| Log(assets) | | | | | -0.105 | -2.98** |
| Fund age | | | | | -0.009 | -0.38 |
| Lambda | -0.052 | -0.55 | -0.053 | -0.55 | -0.026 | -0.29 |
| Adj. R-squared | 0.00 | | 0.00 | | 0.01 | |
| Num Obs. | 320 | | 320 | | 320 | |

**Panel B: Post-DD Report Alpha Difference**

| | Model 1 | | Model 2 | | Model 3 | |
|---|---|---|---|---|---|---|
| | Coeff. | *t*-value | Coeff. | *t*-value | Coeff. | *t*-value |
| Intercept | -0.411 | -0.54 | -0.414 | -0.57 | 4.785 | 4.13** |
| Omega | -0.248 | -2.86** | -0.255 | -2.80** | -0.299 | -3.24** |
| Prior Std. Dev. | -0.096 | -0.60 | -0.058 | -0.32 | -0.027 | -0.15 |
| Omega* Std. Dev. | -0.056 | -3.22** | -0.057 | -3.20** | -0.064 | -3.53** |
| Directional Traders | | | 0.146 | 2.94** | 0.095 | 1.35 |
| FOF | | | 0.219 | 1.43 | 0.414 | 2.79** |
| Managed Futures | | | 0.687 | 2.94** | 0.220 | 0.79 |
| Multi-Process | | | 0.207 | 4.24** | 0.370 | 12.49** |
| Relative Value | | | 0.325 | 2.67** | 0.408 | 3.77** |
| Log(assets) | | | | | -0.254 | -3.84** |
| Fund age | | | | | 0.035 | 0.97 |
| Lambda | -0.091 | -0.45 | -0.105 | -0.42 | -0.380 | -1.44 |
| Adj. R-squared | 0.00 | | 0.00 | | 0.02 | |
| Num Obs. | 218 | | 218 | | 218 | |

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**Table 1: Basic Statistics**

This table reports summary statistics for our sample. Characteristic data concerning fund properties, operations, and background issues are hand-collected from DD reports while performance data are collected from TASS, CISDM, and the DD reports. The term *N* represents the number of observations, *Mean* is the mean value, *Std. Dev.* is the standard deviation, and *Min* and *Max* are the minimum and maximum values, respectively. Here AUM stands for assets under management, and NAV is net asset value. Data definitions are reported in Appendix A.

| Performance | N | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| Avg. returns | 419 | 1.67 | 1.18 | -1.97 | 9.73 |
| Return std. dev. | 417 | 2.37 | 1.81 | 0.01 | 12.40 |
| Autocorrelation | 393 | 0.15 | 0.23 | -0.55 | 0.78 |
| Appraisal ratio | 336 | 1.05 | 2.33 | -0.61 | 37.49 |
| Fund Properties | | | | | |
| Management fee (%) | 441 | 1.54 | 0.48 | 0.00 | 3.50 |
| Incentive fee (%) | 440 | 19.13 | 4.50 | 0.00 | 50.00 |
| High water mark | 439 | 0.97 | 0.18 | 0.00 | 1.00 |
| Redemption period | 441 | 72.25 | 74.97 | 1.00 | 730.00 |
| Lockup period | 441 | 97.01 | 199.15 | 0.00 | 2000.00 |
| Notice period | 442 | 50.36 | 35.84 | 1.00 | 365.00 |
| AUM ($ millions) | 441 | 380.62 | 861.55 | 0.00 | 8000.00 |
| Operations | | | | | |
| Pricing | 443 | 0.65 | 0.48 | 0.00 | 1.00 |
| Signature: bank | 404 | 1.70 | 0.71 | 0.00 | 4.00 |
| Signature: prime broker | 392 | 1.74 | 0.73 | 0.00 | 5.00 |
| Signature: IQ | 438 | 0.25 | 0.44 | 0.00 | 1.00 |
| Big4Auditor | 443 | 0.63 | 0.48 | 0.00 | 1.00 |
| Money restrictions | 384 | 0.38 | 0.48 | 0.00 | 1.00 |
| NAV restate | 442 | 0.10 | 0.30 | 0.00 | 1.00 |
| Staff departure | 437 | 0.49 | 0.95 | 0.00 | 7.00 |
| % of board Ind. | 338 | 0.45 | 0.32 | 0.00 | 1.00 |
| Background Issues | | | | | |
| Problem | 443 | 0.41 | 0.49 | 0.00 | 1.00 |
| Lawsuit | 443 | 0.32 | 0.47 | 0.00 | 1.00 |
| Regulatory | 443 | 0.15 | 0.36 | 0.00 | 1.00 |
| Misrepresentation | 443 | 0.21 | 0.41 | 0.00 | 1.00 |
| Inconsistency | 443 | 0.28 | 0.45 | 0.00 | 1.00 |
| Noted verification problem | 443 | 0.42 | 0.49 | 0.00 | 1.00 |

**Table 2: Univariate Information on Verification Problems**

This table provides further univariate information on background issues based on information contained in the DD reports. Here *Verification Problem* provides further detail on *Inconsistencies* reported in Table I, while *Noted Misstatements* provides further information regarding *Misrepresentations*. The term *N* represents the number of observations, *Mean* is the mean value, *Std. Dev.* is the standard deviation, and *Min* and *Max* are the minimum and maximum values, respectively. Data definitions are reported in Appendix A.

| Verification Problems | N | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| Signature Disagreement | 443 | 16.03% | 36. 73% | 0 | 1 |
| Pricing Disagreement | 443 | 3.62% | 18.68% | 0 | 1 |
| Bad Recall | 443 | 20.99% | 40.77% | 0 | 1 |
| Assets Disagree | 443 | 10.38% | 30.54% | 0 | 1 |
| Performance Disagree | 442 | 4.52% | 20.81% | 0 | 1 |
| Switched Vendor | 443 | 11.51% | 31.95% | 0 | 1 |
| Refused DD Question | 443 | 14.00% | 34.73% | 0 | 1 |
| Can't Verify Assets | 443 | 8.13% | 27.35% | 0 | 1 |
| Can't Verify Performance | 443 | 9.03% | 28.69% | 0 | 1 |

| Noted Misstatements | N | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| Strategic Misstatement | 443 | 6.32% | 24.36% | 0 | 1 |
| Misstatement | 443 | 9.26% | 29.01% | 0 | 1 |
| Truth teller | 443 | 23.48% | 42.43% | 0 | 1 |
| | | | | | |
| Regulatory Misstatement | 443 | 6.32% | 24.36% | 0 | 1 |
| Lawsuit Misstatement | 443 | 17.38% | 37.94% | 0 | 1 |
| Legal Misstatement | 443 | 2.26% | 14.87% | 0 | 1 |
| Background Misstatement | 443 | 5.87% | 23.53% | 0 | 1 |

## Table 3: Comparison of Problem and Non-Problem Funds

This table examines univariate differences of Non-Problem and Problem funds. Data definitions are reported in Appendix A, and AUM stands for assets under management and NAV is net asset value. Here *Problem* funds are those funds that have either a regulatory issue or a lawsuit discussed on the DD report, while *Non-Problem* funds do not have such disclosures. The number of observations (*N*) and the mean value (*Mean*) for both groups is presented. Here *Diff* is the difference between the two groups, with positive values indicating higher values for the *Non-Problem* group, and vice versa. The significance of the difference is assessed using a *t*-test, and ** and * indicate significance at the 1% and 5% levels, respectively.

| | Non-Problem | | Problem | | |
|---|---|---|---|---|---|
| Performance | N | Mean | N | Mean | Diff |
| Avg. Returns | 242 | 1.65 | 177 | 1.70 | -0.05 |
| Return std. dev. | 240 | 2.29 | 177 | 2.47 | -0.18 |
| Autocorrelation | 227 | 0.14 | 166 | 0.15 | -0.01 |
| Appraisal ratio | 198 | 0.95 | 138 | 1.20 | -0.25 |
| Fund Properties | | | | | |
| Management fee (%) | 258 | 1.57 | 183 | 1.50 | 0.07 |
| Incentive fee (%) | 259 | 19.19 | 182 | 19.05 | 0.14 |
| High water mark | 256 | 0.98 | 183 | 0.96 | 0.02 |
| Redemption period (days) | 260 | 64.41 | 181 | 83.51 | -19.10* |
| Lockup period (days) | 260 | 76.77 | 181 | 126.08 | -49.31* |
| Notice period (days) | 260 | 47.65 | 182 | 54.23 | -6.58 |
| AUM ($ millions) | 260 | 282.12 | 181 | 522.11 | -239.99* |
| Operations | | | | | |
| Pricing | 260 | 0.72 | 183 | 0.54 | 0.18** |
| Signature: IQ | 256 | 0.26 | 182 | 0.25 | 0.01 |
| Big4Auditor | 260 | 0.70 | 183 | 0.52 | 0.18** |
| Money restrictions | 221 | 0.40 | 163 | 0.34 | 0.06 |
| NAV restate | 259 | 0.10 | 183 | 0.10 | 0.00 |
| Staff departure | 258 | 0.42 | 179 | 0.58 | -0.16 |
| % of board Ind. | 214 | 0.47 | 124 | 0.43 | 0.04 |
| Background Issues | | | | | |
| Misrepresentation | 260 | 0.10 | 183 | 0.38 | -0.28** |
| Inconsistency | 260 | 0.27 | 183 | 0.30 | -0.03 |
| Noted ver problem | 260 | 0.34 | 183 | 0.54 | -0.20** |
| Signature Disagreement | 260 | 0.17 | 183 | 0.15 | 0.02 |
| Pricing Disagreement | 260 | 0.04 | 183 | 0.03 | 0.01 |
| Bad Recall | 260 | 0.20 | 183 | 0.22 | -0.02 |
| Assets Disagree | 260 | 0.08 | 183 | 0.14 | -0.06 |
| Performance Disagree | 260 | 0.04 | 182 | 0.05 | -0.01 |
| Switched Vendor | 260 | 0.07 | 183 | 0.18 | -0.11** |
| Refused DD Question | 260 | 0.13 | 183 | 0.15 | -0.02 |
| Can't Verify Assets | 260 | 0.09 | 183 | 0.07 | 0.02 |
| Can't Verify Performance | 260 | 0.09 | 183 | 0.09 | 0.00 |

**Table 4: Relation between Past Problems and Operational Risk Variables**

This table reports the results of logistic models investigating the relation between operational risk variables and problems defined as lawsuits and regulatory issues. The dependent variable is one if the fund has a past legal or regulatory issue, and zero otherwise. Positive values indicate a fund is more likely to have a problem. Models are run with style dummies to control for style effects. Models are run in connection with a two-stage Heckman (1979) model, where *Lambda* is the control term. Variables definitions are in Appendix A. Here ** and * indicate significance at the 1% and 5% levels, respectively.

| | Model 1 | | Model 2 | |
|---|---|---|---|---|
| | Coefficient | Chi sq. | Coefficient | Chi sq. |
| Return mean | 0.183 | 0.90 | 0.033 | 0.02 |
| Return std. dev. | 0.038 | 0.11 | 0.087 | 0.45 |
| Return autocorr | 0.030 | 0.00 | -0.140 | 0.04 |
| Log(assets) | 0.089 | 0.95 | 0.159 | 2.01 |
| Fund age | 0.033 | 0.33 | 0.052 | 0.60 |
| Management fee | -0.473 | 2.71 | -0.280 | 0.62 |
| Incentive fee | -0.027 | 0.89 | -0.014 | 0.18 |
| Lockup period | 0.006 | 0.07 | 0.014 | 0.29 |
| Notice period | 0.002 | 0.38 | -0.002 | 0.15 |
| Background Misstatement | 0.029 | 0.00 | 0.259 | 0.16 |
| Signature IQ | -0.024 | 0.01 | -0.170 | 0.19 |
| Pricing | -0.698 | 6.80** | -0.905 | 6.92** |
| Big 4 auditor | -0.817 | 7.34** | -0.882 | 5.11* |
| Perf Ver Issue | -0.111 | 0.11 | 0.121 | 0.09 |
| Bad Recall | -0.062 | 0.04 | -0.476 | 1.35 |
| Oper Ver Issue | 0.001 | 0.00 | -0.393 | 1.00 |
| Vendor Switch | 1.296 | 10.39** | 1.568 | 12.49** |
| Refused DD Question | 0.218 | 0.40 | 0.449 | 1.19 |
| # Ind Board | | | -0.521 | 1.10 |
| Lambda | 0.452 | 1.10 | 0.218 | 0.20 |
| | | | | |
| Pseudo R-squared | 0.21 | | 0.27 | |
| Num Obs. | 382 | | 290 | |

## Table 5: Canonical Correlation between TASS and DD Variables

This table reports the results of a canonical analysis relating operational risk DD data to the observable TASS/CISDM data. The canonical analysis is based on a consistent estimator of the unconditional covariance matrix of the variables using a Heckman (1979) procedure adapted to this multivariate extension. It uses the information contained in the DD report to construct a univariate measure of operational risk, or $\omega$-score, based on the linear combination implied by the DD canonical variate that is maximally correlated with the set of TASS variables considered. See Appendix A for the DD variable definitions. Here ** and * indicate significance at the 1% and 5% levels, respectively.

| TASS/CISDM Variables | | DD Variables | |
|---|---|---|---|
| Previous Returns | -0.02 | Misstatements | 0.56** |
| Previous Std. Dev. | -0.25** | SignIQ | -0.15** |
| First-Order AC | -0.70** | Big4Auditor | -0.68** |
| Fund Age | -0.28** | Pricing | -0.48** |
| Log of Assets | -0.24** | Internal Accounting | 0.18** |
| Management Fee | -0.12* | Misstatements*SignIQ | 0.32** |
| Incentive Fee | -0.05 | Misstatements*Big4Auditor | 0.22** |
| Leverage | -0.59** | Misstatements*Pricing | 0.09 |
| Lockup | 0.14** | Misstatements*Internal Accounting | 0.75** |
| Advance Notice | 0.12* | | |
| | | | |
| Correlation between TASS and DD Panels | 0.47** | | |

**Table 6: Relation between the Post-Appraisal Ratio and Operational Risk Measure $\omega$-Score**

Investigating the relation between the appraisal ratio measured after the DD report and risk measures computed as of the date of the DD report, this table reports *t*-values computed on clustered (on style of management) standard errors. The standard deviation is the natural logarithm of the monthly return standard deviation up to but not including the report dates. Both DD funds and their related funds are included in the analysis. The fund appraisal ratio, computed using the Fung–Hsieh (2004) seven-factor model using returns after the DD report, is the dependent variable. Models are run in connection with a two-stage Heckman (1979) model, where *Lambda* is the inverse Mills ratio. Here ** and * indicate significance at the 1% and 5% levels, respectively.

| | Model 1 | | Model 2 | | Model 3 | |
|---|---|---|---|---|---|---|
| | Coeff. | *t*-value | Coeff. | *t*-value | Coeff. | *t*-value |
| Intercept | -1.761 | -3.57** | -1.872 | -4.19** | -0.803 | -2.47* |
| Omega | -0.256 | -2.68** | -0.249 | -2.52* | -0.263 | -2.53* |
| Prior Std. Dev. | -0.444 | -3.65** | -0.487 | -4.51** | -0.486 | -4.51** |
| Omega* Std. Dev. | -0.064 | -2.66** | -0.063 | -2.58* | -0.066 | -2.59** |
| Directional Traders | | | -0.070 | -3.20** | -0.043 | -2.05* |
| FOF | | | -0.483 | -6.48** | -0.465 | -6.76** |
| Managed Futures | | | 0.276 | 11.59** | 0.215 | 8.60** |
| Multi-Process | | | 0.052 | 1.56 | 0.094 | 3.83** |
| Relative Value | | | -0.071 | -1.17 | -0.018 | -0.36 |
| Log(assets) | | | | | -0.061 | -2.97** |
| Fund age | | | | | -0.003 | -0.47 |
| Lambda | 0.073 | 2.86** | 0.074 | 2.84** | 0.090 | 3.90** |
| Adj. R-squared | 0.30 | | 0.31 | | 0.31 | |
| Num Obs. | 320 | | 320 | | 320 | |

**Table 7: Relation between Operational Risk Measure $\omega$-Score and Fund Death**

This table reports the result of a logistic regression that explains the incidence of fund death as a function of high levels of operational risk, financial risk and fund style over the period of our DD sample, January 2003 – August 2008. Using the canonical correlation results reported in Table V, we construct an $\omega$-Score for every $US fund alive as of January 2003 in the Lipper-TASS database with at least 12 months of contiguous data to compute prior mean, standard deviation and autocorrelation coefficients, and take other fund characteristics defined as of that date. High operational risk is defined as funds with an $\omega$-Score higher than the median score as of that date. The standard deviation is the natural logarithm of the monthly return standard deviation prior to January 2003. Fund death is defined according to the most recent edition of the TASS database as funds which TASS is unable to contact, which are liquidated, dormant, where the fund is closed down or where TASS is unable to determine the reason for the failure to report data. Funds that are closed to new investment, which have merged into another entity or have merely stopped reporting to TASS are deemed to be "alive" for this purpose. Fund styles are based on TASS definitions. Here ** and * indicate significance at the 1% and 5% levels, respectively.

| | Model 1 | | Model 2 | |
|---|---|---|---|---|
| | Coeff. | *t*-value | Coeff. | *t*-value |
| Intercept | -2.927 | -4.70** | -3.268 | -4.88** |
| High Operational Risk | 2.261 | 2.47* | 2.385 | 2.56* |
| Std. Dev. | -0.434 | -2.60** | -0.543 | -2.80** |
| High Op. Risk*Std. Dev | 0.711 | 2.83** | 0.757 | 2.94** |
| Convertible Arbitrage | | | -0.374 | -0.71 |
| Dedicated Short Bias | | | 0.433 | 0.53 |
| Emerging Markets | | | 0.138 | 0.28 |
| Equity Market Neutral | | | 0.316 | 0.74 |
| Event Driven | | | -0.674 | -1.40 |
| Fixed Income Arbitrage | | | -0.107 | -0.21 |
| Fund of Funds | | | -0.173 | -0.52 |
| Global Macro | | | 0.900 | 1.93 |
| McFadden Pseudo $R^2$ | 0.018 | | 0.032 | |
| Num Obs. | 631 | | 631 | |
| Percent Dead | 18% | | 18% | |

**Table 8: Relation between Future Investor Flows and Operational Risk Measure $\omega$-Score**

This table reports *t*-values computed on clustered (on investment styles) standard errors examining investor flows after the DD report. The dependent variable is the fund's flow computed as the percentage change in prior assets over the 12 months after the DD report, after controlling for organic growth. Each DD fund's performance is ranked against other funds available at the time of the DD report. Models are run in connection with a two-stage Heckman (1979) model, where *Lambda* is the control term. Here ** and * indicate significance at the 1% and 5% levels, respectively.

| | Model 1 | | Model 2 | |
|---|---|---|---|---|
| | Coefficient | *t-values* | Coefficient | *t-values* |
| Intercept | 3.998 | 1.96* | 4.122 | 1.93 |
| Low Rank | 4.055 | 0.95 | 4.255 | 1.39 |
| Mid Rank | -0.943 | -0.30 | -1.031 | -0.46 |
| High Rank | 3.477 | 2.71** | 3.084 | 2.66** |
| Omega | -0.021 | -0.78 | 0.006 | 0.03 |
| Log(assets) | -0.363 | -2.66** | -0.368 | -2.79** |
| Prior Std. Dev. | -0.386 | -6.43** | -0.378 | -5.77** |
| Low Rank*omega | | | -0.019 | -0.02 |
| Mid Rank*omega | | | -0.002 | -0.01 |
| High Rank*omega | | | -0.203 | -1.02 |
| Lambda | 0.298 | 3.29** | 0.298 | 3.68** |
| | | | | |
| Adjusted R-Squared | 0.13 | | 0.12 | |
| Num Obs. | 250 | | 250 | |

**Table 9: Comparison of Investor Flows and Post-DD Appraisal Ratios**

This table reports the results of comparing the flows and appraisal ratios of funds selected for DD reports and other matched funds from our combined TASS/CISDM database. Funds for the appraisal ratio results were matched by age, size, and prior appraisal ratio. The matching fund was selected as the fund with the lowest total difference across all three variables, with the prior appraisal ratio receiving twice as much weight. Match funds for the flow results were selected by age, assets, and return performance over the prior period. The matching fund was selected as the fund with the lowest total difference across all three variables, with prior return performance receiving twice as much weight. The results for all DD funds, problem funds, and non-problem funds are reported, as well as *p*-values for the difference.

| | DD Funds | Non-DD-Matched Funds | Difference | *p*-value |
|---|---|---|---|---|
| Flows | 1.478 | 0.626 | 0.852 | 0.00 |
| Problem Flows | 1.712 | 0.739 | 0.973 | 0.00 |
| Non-Problem Flows | 1.237 | 0.510 | 0.728 | 0.00 |
| | | | | |
| Appraisal Ratio | 0.212 | 0.137 | 0.074 | 0.31 |
| Problem Funds | 0.243 | 0.191 | 0.051 | 0.70 |
| Non-Problem Funds | 0.183 | 0.088 | 0.095 | 0.18 |